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1 Chemoinformatics-driven design of new physical
2 solvents for selective CO₂ absorption

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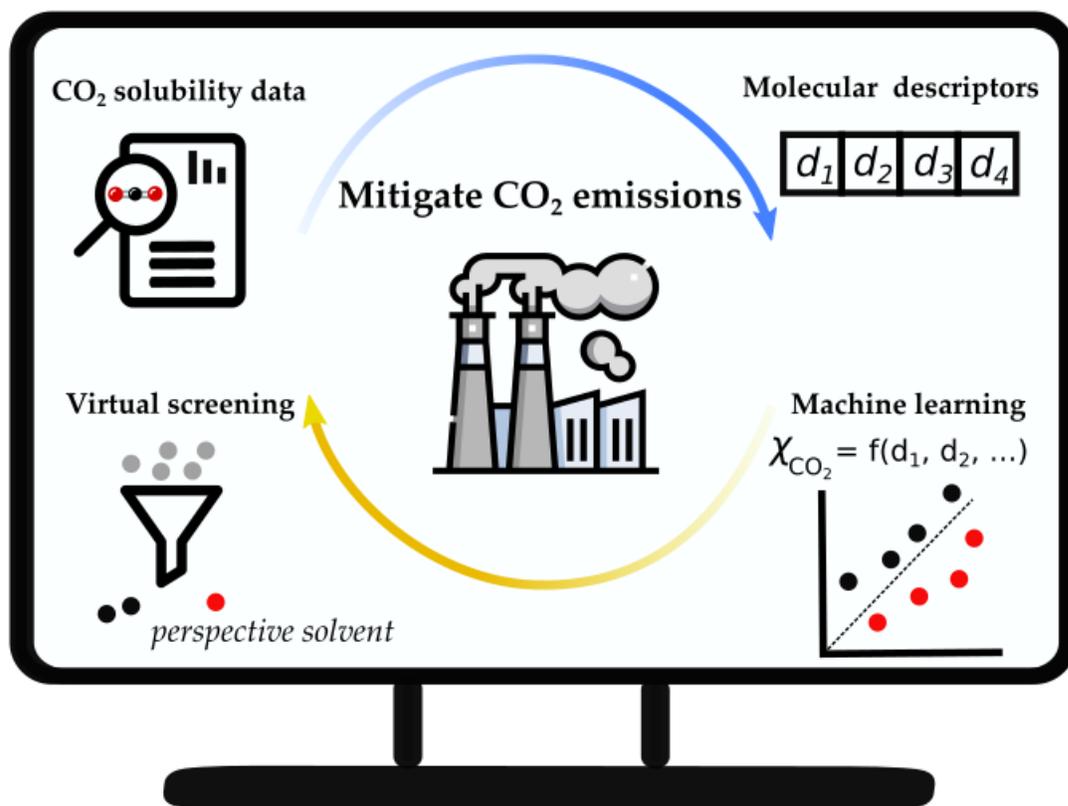
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11 *Keywords: gas solubility, industrial gases, carbon dioxide, methane, nitrogen, hydrogen, carbon*
12 *monoxide, chemoinformatics, machine learning*

13

14 TOC GRAPHIC



15

16 **ABSTRACT**

17 The removal of CO₂ from gases is an important industrial process in the transition to a low-
18 carbon economy. The use of selective physical (co-)solvents is especially perspective in cases
19 when the amount of CO₂ is large as it enables one to lower the energy requirements for solvent
20 regeneration. However, only a few physical solvents have found industrial application and the
21 design of new ones can pave the way to more efficient gas treatment techniques. Experimental
22 screening of gas solubility is a labor-intensive process, and solubility modeling is a viable
23 strategy to reduce the number of solvents subject to experimental measurements. In this paper, a
24 chemoinformatics-based modeling workflow was applied to build a predictive model for the
25 solubility of CO₂ and four other industrially important gases (CO, CH₄, H₂, N₂). A dataset
26 containing solubilities of gases in 280 solvents was collected from literature sources and
27 supplemented with the new data for six solvents measured in the present study. A modeling
28 workflow based on the usage of several state-of-the-art machine learning algorithms was applied
29 to establish quantitative structure-solubility relationships. The best models were used to perform
30 virtual screening of the industrially produced chemicals. It enabled the identification of
31 compounds with high predicted CO₂ solubility and selectivity towards the other gases. The
32 prediction for one of the compounds – 4-Methylmorpholine was confirmed experimentally.

33 **SYNOPSIS STATEMENT**

34 Developing better solvents for selective CO₂ capture is crucial for reaching net-zero emissions
35 targets.

36 INTRODUCTION

37 Global warming due to increasing levels of greenhouse gases CO₂ and CH₄ in the atmosphere
38 has become a major public issue. Several companies and countries have announced ambitious
39 plans to reach net zero CO₂ emissions by 2050. According to the International Energy Agency,
40 Carbon Capture, Utilization or Storage (CCUS) will likely play an important role in achieving
41 this goal.¹ Numerous materials for CO₂ capturing from gases were suggested, including chemical
42 and physical solvents, zeolites, metal oxides, metal-organic frameworks, and membranes.^{2,3} The
43 applicability of a certain technology in each case depends on many factors, including the
44 concentrations of CO₂ and of other components in the gas, the pressure of the gas feed, the
45 temperature, etc. In cases, wherein the partial pressure of CO₂ in a gas mixture is sufficiently
46 large, physical solvents represent a perspective alternative to the conventionally used aqueous
47 amines mixtures because of the lower energy requirement. Indeed, a large part of a physical
48 solvent can be regenerated by pressure swing and air stripping, while the regeneration of
49 chemical solvents requires heating and steam stripping^{3,4} Pre-combustion CO₂ capture is a key
50 example of a case with a CO₂ partial pressure sufficiently high to use physical solvents. In a pre-
51 combustion process the feed (e.g. coal, natural gas, biomass, etc.) is converted into syngas (H₂
52 and CO) via gasification, steam reforming, auto thermal reforming or partial oxidation and
53 subsequently the CO is further converted into CO₂ and H₂ via the water gas shift reaction.
54 Typical CO₂ concentrations are in the range of 15 to 60 mol% for a total pressure of 2 to 7 MPa,
55 thus, the CO₂ can be captured with a physical solvent⁵. The other components are mainly H₂, but
56 also CO, N₂, CH₄, H₂O (saturation). The composition strongly depends on the feedstock and on
57 the process. At the moment, only a limited number of physical solvents such as methanol
58 (Rectisol® process), propylene carbonate (Fluor® process), N-acetyl and N-formyl morpholines

59 (Morphysorb® process), 1-methylpyrrolidin-2-one (Purisol® process), polyethylene glycol
60 ethers (Selexol® process), found application in the industrial CO₂ capture processes. Physical
61 solvents are also often added to chemical solvents (so-called hybrid solvents), for example, to
62 increase the selectivity of absorption towards a specific gas component, to lower the regeneration
63 energy, etc. Examples are sulfolane (Sulfinol® process), thiodiglycol (Hysweet ® process), etc.
64 The search for new physical (co-)solvents is thus an important task.⁶

65 New suitable solvents should satisfy many criteria, among which are a decent capacity to
66 absorb CO₂, a competitive price, a low volatility (to avoid solvent losses), a low viscosity, etc.
67 Another very important criterium is the selectivity towards CO₂ which should be high enough to
68 obtain a CO₂ stream of acceptable purity for re-utilization or storage, and to avoid losses of
69 valuable chemicals like CH₄. Depending on the source of the CO₂, the selectivity criteria are
70 different. For the removal of CO₂ from natural gas the co-absorption of mainly CH₄, but also of
71 N₂ and H₂O and eventually H₂S should be limited. For a steam methane reformer (SMR), which
72 in a near future is likely to play a key role in the massive production of blue hydrogen from
73 natural gas, the absorption of CO₂ with a high selectivity towards H₂ is important^{7,8}, but also
74 towards CO, H₂O, N₂ and CH₄^{7,8}. The CO₂ present in flue gas from boilers should be removed
75 with a high selectivity towards N₂, but the co-absorption of water and SO_x, NO_x should be low
76 too.

77 Experimental screening of gas solubility is a time and labor-intensive process, and solubility
78 modeling is a viable strategy to reduce the costs of the required experiments. There were
79 numerous approaches suggested for modeling gas solubility in pure physical solvents. In the
80 work by Pirig et al.⁹ a five-parameter linear equation based on the experimentally measured
81 properties was used to model the solubility in 58 solvents. In the work by Li et al.¹⁰, artificial

82 neural networks were used to model CO₂ mole fraction solubility in 11 solvents (alcohols, ethers,
83 ketones) at different temperatures and pressures. Several structural features (number of C-H, O-
84 H, C-O, C=O bonds, number of rotatable bonds, etc.) and physical properties of the compounds
85 (density, dipole moment, etc.) were used as descriptors. It enabled achieving high precision of
86 predictions for certain types of physical solvents under varying experimental conditions.
87 Nonetheless, the major disadvantage of the modeling approaches based on experimentally
88 measured parameters – the limited number of compounds for which the parameters are available,
89 complicates their usage for large-scale virtual screening of solvent candidates.

90 Alternative strategies for modeling CO₂ solubility, that require less preliminary knowledge of
91 the experimental properties, were also suggested. In the works of Li et al.¹¹ and Shi et al.¹²
92 molecular simulations were used to predict CO₂ solubility in nine and twenty-seven physical
93 solvents respectively. Although high predictive accuracy was achieved in both works, molecular
94 simulations are also not very convenient for the large-scale virtual screening, as they are time-
95 consuming and require significant computational resources. Alternatively, the conductor-like
96 screening model for real solvents (COSMO-RS),¹³ a method combining quantum chemical
97 calculations with statistical thermodynamics, was suggested to rapidly screen large sets of
98 various materials. In the work by Kim et al.¹⁴ CO₂ and CH₄ Henry's law coefficients were
99 predicted by COSMO-RS for 63 common liquid solvents and 10 ionic liquids at 300 K.
100 Unfortunately, there was no comparison of the predicted solubilities with the available
101 experimental data.

102 A pool of gas solubility data accumulated in scientific literature supports applying machine
103 learning for quantitative structure-solubility relationships (QSPR) modeling. In this approach
104 chemical structures of compounds are encoded as vectors of molecular descriptors and machine

105 learning algorithms are then applied for modeling the property of interest. As compared to the
106 modeling based on the usage of experimentally determined parameters or resource-intensive
107 molecular simulations, this method allows efficient screening of large numbers of compounds.
108 To our knowledge, there was only one work related to QSPR modeling of CO₂ solubility in
109 physical solvents published.¹⁵ In the paper of Gorji et al.,¹⁵ Henry coefficients for 22 solvents
110 composed only of carbon, oxygen, and hydrogen elements at different temperatures were used to
111 build a multiple linear regression model with Dragon¹⁶ descriptors. Although good predictive
112 performance was achieved, the applicability domain (AD) of this model is limited to the specific
113 classes of compounds used for model building. Except for recent publications on H₂S solubility
114 modeling^{17,18}, to our knowledge there were no papers describing the application of the
115 chemoinformatics-driven methods for physical solubility modeling of the major components
116 encountered in natural gas treatment or in the pre-combustion CO₂ capture process : carbon
117 dioxide (CO₂), methane (CH₄), carbon monoxide (CO), hydrogen (H₂), and nitrogen (N₂). Hence,
118 the investigation of the perceptiveness of using chemoinformatics for the rational design of new
119 solvents for the absorption of CO₂ and other industrial gases is an important task.

120

121 **MATERIALS AND METHODS**

122 *Data collection and preprocessing*

123 A dataset containing mole fraction solubility values (χ) for 280 liquid solvents at 298.15 K and
124 1 atm was collected (Table S1, Supporting Information) from IUPAC reports¹⁹⁻²³, scientific
125 literature²⁴⁻⁷⁵, and patents^{76,77}. The mole fraction solubility for a binary (gas-liquid) system is
126 defined¹⁹ as:

127
$$\chi = \frac{n(g)}{n(g)+n(l)} \quad (1)$$

128 $n(g)$ – an amount of substance in a gas phase, $n(l)$ – an amount of substance in a liquid phase.

129 Median values were then taken for the solvents associated to several reliable measurements of
130 χ at the particular temperature. The final dataset used for modeling is present in Table S1
131 (Supporting Information). Extrapolation and interpolation of the data to 298.15 K were
132 performed assuming a linear variation of Henry's coefficients with temperature or by the
133 equations suggested in the IUPAC report or corresponding papers. The compounds that are
134 structural outliers with respect to the training set majority, comprising water, carbon disulfide,
135 octamethylcyclotetrasiloxane and hydrazines were not included to the dataset. These compounds
136 contain rare or unique fragments significantly affecting their gas-absorbing properties, and,
137 hence, confident predictions cannot be obtained for them by statistical modeling.

138 The collected mole fraction solubilities were converted to the Kuenen coefficients S using the
139 following formula⁷⁸:

140
$$S = \frac{R \times T \times P}{M_w} \times \frac{\chi}{1 - \chi} \quad (2)$$

141 S – Kuenen coefficient (m^3kg^{-1}), R – ideal gas constant ($8.314 \text{ m}^3\text{PaK}^{-1}\text{mol}^{-1}$), T and P –
142 standard temperature and pressure (273.15 K and 101.325 kPa), M_w – molecular weight of
143 compound (kgmol^{-1}), χ – mole fraction solubility value.

144 The Kuenen coefficient is the volume of saturated gas reduced at 273.15 K and 1 atm pressure,
145 which is dissolved by unit mass of pure solvent at the temperature of measurement and partial
146 pressure of 1 atm. This parameter is widely used in industrial applications, as it enables one to

147 directly estimate the efficiency of the particular solvent related to its cost and dimensions of the
148 required industrial unit (design-capital expenses cost CAPEX). Here, Kuenen coefficients were
149 used for the data analysis and models interpretation.

150 The selectivity index SI was calculated using the following formula:

$$151 \quad SI = \frac{\chi_{CO_2}}{\chi_{gas}} \quad (3)$$

152 SI – selectivity index, experimental or predicted χ_{CO_2} and χ_{gas} – mole fraction solubilities of
153 CO₂ and other gases respectively.

154 All χ values were also transformed to a logarithmic scale, i.e. the negative value of the decimal
155 logarithm was taken (Figure S1).

156 *Modeling*

157 *Standardization*

158 All compound structures were standardized using in-house standardization procedures based
159 on KNIME,⁷⁹ which included aromatization, stereochemistry depletion, etc.

160 *Descriptors*

161 193 different ISIDA fragment descriptor sets were generated using the Fragmentor17
162 software.^{80,81} ISIDA fragments represent either sequences (the shortest topological paths with an
163 explicit representation of all atoms and bonds), atom-centered fragments (all connected atoms to
164 a certain topological distance), or triplets (all the possible combinations of 3 atoms in a graph
165 with the topological distance between each pair indicated). The number of fragments in each set

166 varied from 30-40 (for short sequences of atoms/bonds) to 400-1200 (for long sequences up to 6
167 atoms) for different gases.

168 Quantum chemical descriptors resulted from DFT calculations in the gas phase, with model
169 wB97X-D 6-31G* performed with the Spartan 18.0 program⁸². Default QSAR descriptors
170 available in Spartan including energy, dipole moment, E_{HOMO} , and E_{LUMO} were calculated.

171 *Machine learning algorithms*

172 Random forest (RF): RF algorithm⁸³ implemented in sci-kit learn library (v. 0.22.1)^{84,85} was
173 used. The following hyperparameters were tuning during optimization (grid search): number of
174 trees (100, 300, 1000), number of features (all features, one-third of all features, \log_2 of the
175 number of features), the maximum depth of the tree (5, 10, full tree), bootstrapping (with and
176 without the usage of bootstrap samples for building the tree).

177 XGBoost (XGB): XGBoost algorithm⁸⁶ as implemented in XGBoost python module (v.1.2.0)⁸⁷
178 was used. The following hyperparameters were tuning during optimization (grid search): number
179 of trees (50, 100, 300, 500), number of features (all features, 70% of all features), number of
180 samples (all samples, 70% of all samples), the maximum depth of the tree (3, 5, 10), learning rate
181 (0.3, 0.1, 0.5, 0.05), the minimum sum of instance weight needed in a node (1, 5, 10). All other
182 parameters were left as default.

183 Support vector regression (SVR): SVR algorithm⁸⁸ implemented in sci-kit learn library (v.
184 0.22.1), was used. The descriptors were scaled to the [0,1] range before applying the algorithm.
185 The following hyperparameters were tuning during optimization (grid search): kernel (linear, rbf,

186 poly, sigmoid), kernel coefficient (1, 0.1, 0.01, 0.001, 0.0001), regularization parameter (0.1, 1,
187 10, 100, 1000).

188 *Model validation workflow*

189 The modeling workflow was implemented using sci-kit learn library (v. 0.22.1) in python 3.7
190 scripting language. Identical modeling workflows were used for solubility modeling (expressed
191 as $-\lg \chi$) of all gases. At the first stage of the modeling, a machine learning algorithm: RF, SVR
192 and XGB were tested in 5-fold cross-validation, which was repeated 5 times (Figure S2). For
193 each descriptor set, the model's measures of performance were calculated and several models
194 with a coefficient of determination $Q^2_{CV} \geq 0.7$ were selected for consensus modeling.

195 The following equations were used to calculate the measures of the model's performance in
196 cross-validation:

$$197 \quad Q^2_{CV} = \frac{\sum_{j=1}^5 \left(1 - \frac{\sum_{i=1}^n (y_{i,exp} - y_{i,pred})^2}{\sum_{i=1}^n (y_{i,exp} - \bar{y})^2}\right)}{5} \quad (4)$$

$$198 \quad RMSE_{CV} = \frac{\sum_{j=1}^5 \sqrt{\frac{\sum_{i=1}^n (y_{i,exp} - y_{i,pred})^2}{n}}}{5} \quad (5)$$

$$199 \quad MAE_{CV} = \frac{\sum_{j=1}^5 \sum_{i=1}^n \frac{|y_{i,exp} - y_{i,pred}|}{n}}{5} \quad (6)$$

200 Above, n is the number of compounds in the entire learning set, $y_{i,exp}$, $y_{i,pred}$ experimental and
201 values predicted in 5-fold cross-validation for compound i from the learning set, j is the index of
202 the repetition of the 5-fold cross-validation procedure. For each measure of the model's
203 performance, the standard deviation over 5 repetitions was calculated.

204 Each of the selected models was then associated with an Applicability Domain (AD), defined
205 as a bounding box.⁸⁹ Hence, the pool of selected models extracted from the given data set was
206 used as a consensus predictor, returning for each input solvent candidate a mean value of
207 solubility estimates and its standard deviation, taken over the predictions returned by each model
208 in the pool, if the compounds appeared outside AD of all the models, or, alternatively, over the
209 predictions returned by only those models having the candidate within their AD.

210 Outlying data points were defined as the data points for which absolute errors ($|\chi_{\text{exp}} - \chi_{\text{pred}}|$)
211 from cross-validation were larger than $2 \times \text{RMSE}_{\text{CV}}$ threshold.

212 *Y-randomization test*

213 The absence of chance correlation was checked through the Y-randomization procedure. Y-
214 randomization test was performed in the following way: $-\lg\chi$ values (y values) were shuffled,
215 surrogate models from the cross-validation were built using shuffled values and the values from
216 the corresponding cross-validation test set were calculated. This procedure was repeated 100
217 times for each fold and the maximum values of the coefficient of determination were compared
218 with the coefficient of determination obtained for the original $-\lg\chi$ values.

219 *Virtual screening*

220 An in-house dataset comprising 4,082 industrially produced compounds and their
221 structural analogs was screened in the following way. Only structures containing the same atoms
222 (C, H, N, O, S, P, halogens) as in the learning set were kept. All structures were standardized and
223 ISIDA descriptors were calculated for them as described above. Individual ISIDA models
224 refitted to the entire dataset with the hyperparameters selected in the cross-validation were used

225 to compose the final consensus model as described above. Then, predictions were made using the
226 ISIDA consensus model. Only compounds that were inside the applicability domain defined as
227 bounding box for at least three ISIDA fragment types were considered.

228 *Software implementation*

229 The developed model was implemented into the ISIDA-Predictor software.⁸¹

230 *Experimental measurement of CO₂ solubility*

231 A “static-synthetic” technique based on a closed-circuit method^{90–92} was used for the
232 determination of CO₂ solubility in the solvents. In this method, which is explained in detail in the
233 supplementary information (Text S1, Figures S3, S4), the system pressure is measured at
234 constant temperature for different overall compositions. To determine the global compositions,
235 the quantities of pure substances charged into the stirred equilibrium cell, which is evacuated and
236 placed in a thermostatic liquid bath, need to be known precisely. The purified and degassed
237 solvents are charged into the cell as compressed liquids using thermostatted piston injectors.
238 Then, the gas is added stepwise as a liquefied gas using the same injection pumps or as a gaseous
239 component using a thermo-regulated gas bomb. Knowing the pressure, temperature, and volume
240 of the gas bomb, the amount of gas inside the bomb can be calculated using correlated PvT data
241 of the gas. Thus, the injected amount of gas can be obtained from the pressure difference in the
242 bomb before and after each injection.

243 Since only temperature, pressure, total loadings, gas-liquid interface level and total volumes
244 are measured, the compositions of the coexisting phases need to be determined by the evaluation
245 of the raw data. From the known amount of solvent, the liquid phase volume is determined using

246 precise information about the density of the liquid solution inside the equilibrium chamber. From
247 the total volume of the cell, the remaining gas phase volume can be calculated precisely (see
248 supplementary information). At given equilibrium conditions (temperature, gas phase volume,
249 and gas pressure) the amounts of gas in the gas phase and thus, also in the liquid phase are
250 obtained. In this approach, several effects influence the resulting liquid phase compositions.
251 These effects are the small amounts of solvents in the gas phase, the compressibility of the
252 solvent under the gas pressure, the partial molar volume of the dissolved gas and the solvent
253 activity coefficient. All effects are considered in an isothermal and isochoric algorithm by
254 solving the mass and volume balances.

255 The partial pressure is obtained during the iterative procedure:

$$256 \quad P_{\text{gas}} = P_{\text{sys}} - P_{\text{solvent}} \quad (6)$$

257 where P_{gas} – partial pressure of the acid gas in the system, P_{sys} – total pressure in the system,
258 P_{solvent} – partial pressure of a solvent vapour. This equation is valid at low pressure and in the
259 absence of chemical reactions in the gas phase. The method to calculate the uncertainty of the
260 measured experimental data is explained in the supplementary information. The uncertainty of
261 the measured CO_2 solubility at 1 atm. is equal or lower than 1%.

262 **RESULTS AND DISCUSSION**

263 *Data collection, preprocessing and analysis*

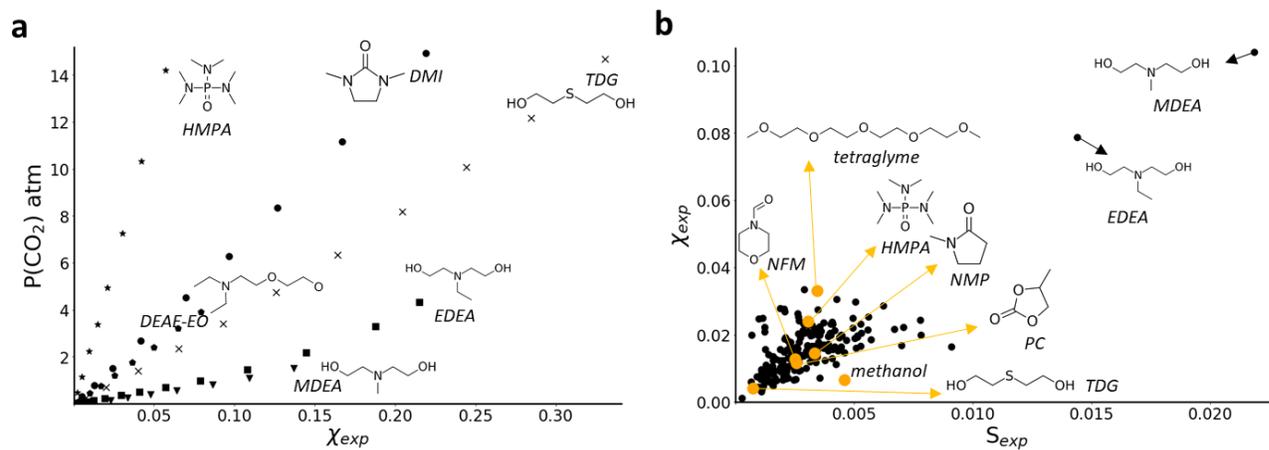
264 IUPAC reports on gas solubilities in non-aqueous solvents contain to our knowledge the most
265 complete and carefully analyzed publicly available data on gas solubility. The data from these
266 reports were used to compose the “cores” of our datasets. As the largest number of data points

267 for various solvents was available at 298.15 K and 1 atm, the data at this temperature and
268 pressure was chosen for modeling. Since the mole fraction values can vary significantly
269 depending on the experimental methods being used, we chose only the data points which were
270 considered as the most reliable by IUPAC's or Total's experts. Data from recent publications
271 either at 298.15 K or obtained by extrapolation or interpolation of the data measured at close
272 temperatures were also added to the dataset.

273 Besides the data collected from IUPAC reports and literature, data points for six compounds,
274 hexametapol (HMPA), 1,3-Dimethylimidazolidin-2-one (DMI), thiodiglycol (TDG), and three
275 tertiary amines 2-[2-hydroxyethyl(methyl)amino]ethanol (MDEA), 2-[ethyl(2-
276 hydroxyethyl)amino]ethanol (EDEA), and 2-[2-(diethylamino)ethoxy]ethanol (DEAE-EO) were
277 measured experimentally and added to the dataset (Figure 1a; Table S1). The choice of the
278 solvents was motivated by their wide application in industrial processes and the absence of
279 consistent data at 298.15 K for them in the literature. TDG is employed in a commercial mixed
280 chemical/physical solvent formulation for sour gas treating (HySWEET technology) developed
281 by TotalEnergies S.E.⁹³ HMPA and DMI are being used as solvents for gases, polymers, and in
282 organic synthesis. Aqueous amines are used as chemical solvents, and only little is known about
283 the physical solubility of gases in pure amines. One of the few examples is MDEA, which, in an
284 aqueous solution, is commonly used for industrial gas treatment, and for which the CO₂ mole
285 fraction solubility can be estimated from Skylogianni.⁹⁴ The value is extremely high (~0.04 at 1
286 atm and 313K) as compared to other physical solvents (see below). Hence, considering the
287 growing interest in water-lean solvents⁹⁵, including the ones based on pure amines⁹⁶, we have
288 chosen three industrial amines (MDEA, EDEA, DEAE-EO) for the experimental assessment of
289 CO₂ physical solubility.

290 All the solvents showed close to linear variation of mole fraction solubility vs partial pressure
291 of the gas in the pressure range 0-2 atm (Figure 1a). Estimated mole fraction solubilities for TDG
292 and DMI (0.0041; 0.0150) are in good agreement with the data that can be obtained by
293 extrapolation from recent publications.^{27,97} On the contrary, CO₂ mole fraction solubility in
294 HMPA (0.024) is lower, than the one suggested by IUPAC's expert¹⁹ (0.031), but is close to the
295 one obtained by Schay et al.¹⁹ (0.028). The mole fractions values in MDEA (0.1) and EDEA
296 (0.08) are remarkably high and in agreement with the aforementioned data for MDEA from the
297 Skylogianni et al. obtained at higher temperatures.⁹⁴ At the same time, the CO₂ solubility in
298 DEAE-EO is much lower (0.02) and is the same as in two other tertiary amines present in the
299 dataset: triethylamine (0.02) and perfluorotributylamine (0.02).

300 The high CO₂ solubility in pure MDEA and EDEA triggers the question whether the
301 absorption is purely physical. It is commonly reported in the literature that, contrary to primary
302 and secondary amines, tertiary amines cannot chemically absorb CO₂ in the absence of water^{98,99}
303 (we have verified that no water was present in the solvent in the experiments performed in the
304 present paper). This view has been challenged by Maddox¹⁰⁰ and more recently by Heldebrandt
305 et al.^{101,102} who studied the reaction of CO₂ with anhydrous tertiary amines. Both conclude that
306 reversible Lewis acid-base adducts are formed at high pressure (note that in this work we
307 compare solubilities at low pressure, 1 atm.). Heldebrandt¹⁰¹ suggests that the difference in
308 absorption capacity between pure amines can be explained by solvent polarity effects. Either
309 way, anhydrous tertiary amines do absorb less CO₂ than aqueous tertiary amines, but some still
310 absorb significant amounts of CO₂.



311
 312 Figure 1. (a) Variation of mole fraction with partial pressure for CO₂ in TDG (×), DMI (★), HMPA (●), MDEA
 313 (▼), EDEA (■), and DEAE-EO (□) at 298.15 K experimentally measured for this paper. (b) Plot of experimental
 314 molecular fraction values (χ_{exp}) vs Kuenen coefficients (S_{exp}) at 298.15 K and 1 atm for CO₂.

315 There were 211 mole fraction solubility values collected for CO₂. The largest mole fraction
 316 CO₂ solubility was for tertiary amines MDEA and EDEA (Figure 1b). Among other classes of
 317 compounds with large CO₂ solubility were phosphoric acid esters, long chain ethers, and esters.
 318 To estimate the efficiency of a solvent related to its cost and dimensions of the required
 319 industrial unit, mole fractions were converted to Kuenen coefficients. MDEA and EDEA also
 320 have the largest Kuenen coefficients. By contrast to the trend observed for mole fractions, the
 321 largest Kuenen coefficient values in other compound classes were for small polar compounds:
 322 nitriles, ketones (acetone, butan-2-one), tetrahydrofuran (THF). Notably, the solvents, which are
 323 used in industrial gas treatment processes are not among the best ones in terms of CO₂ solubility
 324 (Figure 1b).

325 Other gases are less studied as compared to CO₂. There were less than 105 mole fraction
 326 solubility values collected for each of other gases (N₂, H₂, CO, CH₄). It is worth noting, that
 327 polar CO and non-polar CH₄, N₂, H₂ showed similar solubility trends. The largest values were

328 for non-polar compounds, including perfluorated alkanes, and long-chain n-alkanes (Figure S5).
329 The minimal χ values were for polar solvents, such as methanol, *N,N*-dimethylformamide
330 (DMF).

331 The collected experimental data were used to analyze the trends in the selectivity of CO₂
332 absorption towards other gases (Figure S6). The only industrial solvent for which the data were
333 available for all the solvents is methanol, which is not selective at 298.15 K and 1 atm. The
334 industrially used solvents were among the best ones in terms of the CO₂/CH₄ selectivity. The
335 highest selectivity index (SI_{exp}) was for dimethyl sulfoxide (DMSO, SI_{exp}=24) and *N*-formyl
336 morpholine (NFM, SI_{exp}=21). Among other most selective solvents were industrially used
337 propylene carbonate (PC) and *N*-Methyl-2-pyrrolidone (NMP). The large selectivity stems from
338 the extremely low solubility of CH₄ in these solvents. The same observation was made for all
339 other gases: the most selective are the polar solvents, such as DMF, 1,4-dioxane, DMSO, etc.
340 (Figure 1b, Figures S3-S4).

341 *Quantitative structure solubility relationships*

342 Application of the machine learning allowed one to establish quantitative structure-
343 solubility relationships. Reasonable predictive accuracy was achieved in the repeated cross-
344 validation procedure for all the gases (Table 1). None of the models has shown chance
345 correlation in the y-scrambling procedure.

346 Table 1. Performance estimation for modeling of mole fraction solubility expressed as $-\lg\chi$.

Gas	ISIDA consensus models	Q^2_{CV}	RMSE _{CV}	MAE _{CV}
CO ₂	20 RF, 17 XGBoost	0.71±0.01	0.12±0.01	0.08±0.01

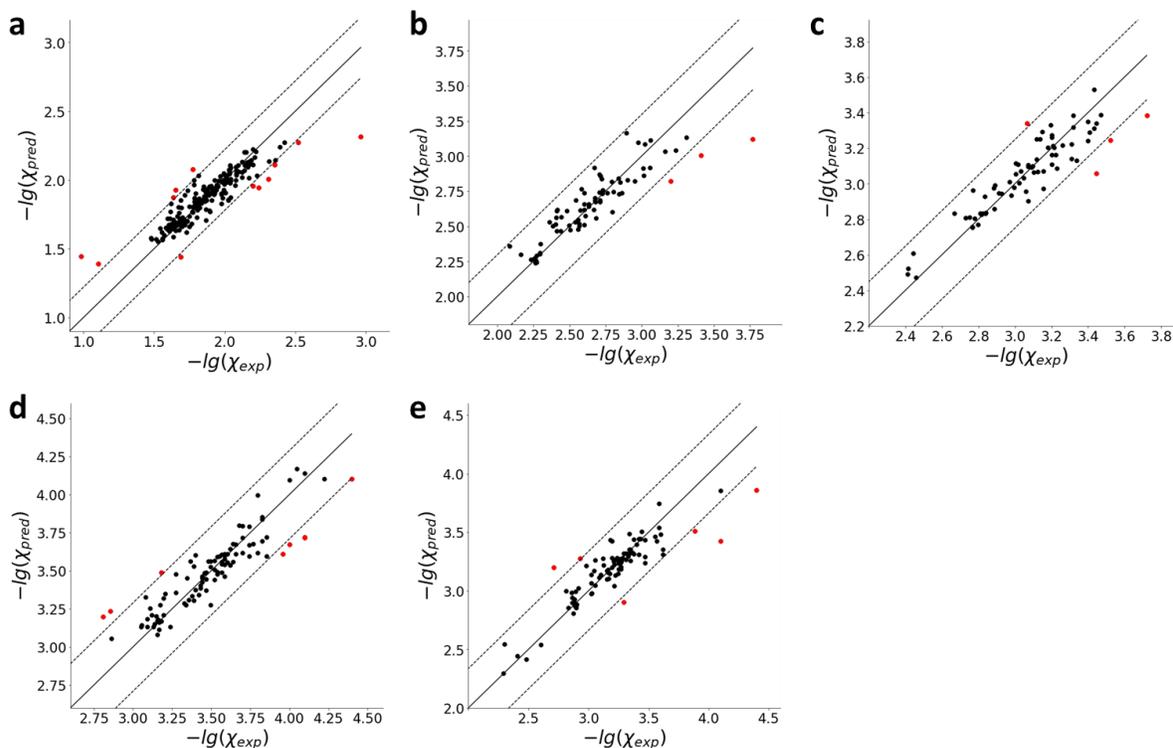
CH ₄	9 SVR, 15 XGBoost	0.77±0.02	0.15±0.01	0.10±0.01
CO	5 SVR, 8 XGBoost	0.78±0.03	0.12±0.01	0.09±0.01
H ₂	2 RF, 3 SVR, 23 XGBoost	0.77±0.04	0.15±0.01	0.10±0.01
N ₂	9 SVR, 12 XGBoost	0.75±0.06	0.17±0.01	0.11±0.01

347

348 Since the collected datasets are small, the presence of compounds containing rare fragments, or
 349 compounds with noise in the experimental data lead to unstable modeling results. Several
 350 compounds, which were systematically mispredicted (the absolute error >0.7 log units) in the
 351 cross-validation procedure were removed: dodecanal and dodecene for the H₂ model, and
 352 dimethyl ether and dodecanal for the CO model. The values for all these compounds are
 353 significantly different from their close structural analogs. They were obtained by interpolation
 354 and additional experimental confirmation is required to assess whether the values are reliable.
 355 After the removal of outliers, the models with reasonable figures of merit were obtained for each
 356 gas (Table 1). The lowest mean absolute error (MAE_{CV}) was for the CO₂ model, which is based
 357 on the largest pool of data. Note, that MAE_{CV} is close to the variance in the experimental data.
 358 For example, the standard deviation for propylene carbonate based on IUPAC's data¹⁹ and the
 359 recently published data³⁶ can be estimated as 0.05 log units.

360 To check if some other descriptor types can lead to significantly better results, we calculated
 361 quantum chemical descriptors using Spartan software. The results of modeling were on average
 362 comparable to those obtained by the usage of ISIDA fragments (Table S2). Considering the
 363 advantages of ISIDA fragments, i.e. speed of calculation and intuitive interpretation of structure-
 364 property relationships, we further focused on this descriptor type.

365 For each model, the compounds for which absolute errors were larger than $2 \times \text{RMSE}_{\text{CV}}$
366 threshold were analyzed (Figure 2, Table S3). These compounds either contain rare fragments or
367 can be considered as “solubility cliffs”: small changes in structure (e.g. replacement of hydrogen
368 atom by methyl group) lead to large changes in solubility (see Figure S7 and discussion below).
369 For example, hexafluorobenzene – the only polyhalogenated aromatic compound and MDEA –
370 one of few representatives of alkanolamines in the dataset were among the compounds with the
371 largest errors for the CO_2 model. The datasets for the gases are rather chemically diverse. Many
372 compounds containing rare fragments appear outside AD of the models in the cross-validation.
373 There were 15% of compounds appearing to be outside AD in the cross-validation for CO_2 ,
374 while about 20-25% of compounds were outside AD for other gases. The presence of compounds
375 with rare fragments leads to high variance of predictions in the cross-validation. From the
376 learning curve (Figure S8), one can see that adding data improves the performance on the
377 validation sets, and, therefore, decreases the gap between prediction accuracy on validation and
378 training sets. Hence, further accumulation of the experimental data on gas solubility organic
379 solvents is required for building more robust models with enlarged applicability domains and the
380 extended range of temperature and pressure values.



381
 382 Figure 2. Plot of predicted ($-\lg\chi_{\text{pred}}$) vs experimental ($-\lg\chi_{\text{exp}}$) values for ISIDA consensus model in cross-
 383 validation procedure for CO_2 (a), CH_4 (b), CO (c), H_2 (d), N_2 (e). The predicted values are calculated as an average
 384 of 5 folds. Compounds for which absolute errors were larger than $2 \times \text{RMSE}_{\text{CV}}$ are shown in red. Dash lines indicate
 385 $\pm 2 \times \text{RMSE}_{\text{CV}}$ threshold.

386
 387 In contrast to the above examples, solubility of CO_2 in alcohols, glycols and ethers was
 388 systematically studied. Yet, one of the largest absolute errors were for glycols (glycerol, ethane-
 389 1,2-diol), which is related to a sharp change in solubility with the replacement of $-\text{OH}$ group to $-$
 390 OCH_3 (Figure S7). For example, the mole fraction solubility in glycerol is more than three-time
 391 smaller, than the solubility in its closest structural analog – propylene glycol (PG). At the same
 392 time solubility in another structural analog – diethylene glycol (DEG), containing the same
 393 number of carbon and oxygen atoms as glycerol, is six time higher. This phenomenon can be

394 explained by considering forces driving the process of gas dissolution. The mechanistic
395 interpretation of this process assumes the formation of a cavity capable of accommodating a gas
396 molecule by breaking solvent-solvent bonds and introduction and fixation of a gas molecule in
397 this cavity due to gas-solvent interactions. Hence, solubility of gases in liquids depends upon two
398 types of interactions: gas-solvent and solvent-solvent.^{103,104} Strong gas-solvent and weak solvent-
399 solvent interactions lead to greater solubility. In line with that, CO₂ solubility in glycols and their
400 ethers follows the cohesive energy density values trend: the solubility is increasing from glycerol
401 to DEG with the decreasing cohesive energy density (glycerol: 1142 MPa; DEG: 615 MPa).¹⁰⁵
402 However, the cohesive energy density is not the only factor affecting the solubility of CO₂.
403 Although carbon dioxide is nonpolar, its appreciable polarizability and ability to accept hydrogen
404 bonds from suitable donor solvents¹⁰⁶ makes structure solubility landscape more complex. For
405 example, CO₂ solubility is lower in hexane than in dimethyl ether of ethylene glycol (DMEG),
406 while the cohesive energy density of DMEG is higher than that of hexane (DMEG: 317 MPa;
407 hexane: 222 MPa)^{105,107}. Thus, the interplay between cohesive energy density and solvent-CO₂
408 interactions should be taken into account in the process of the design of new solvents.

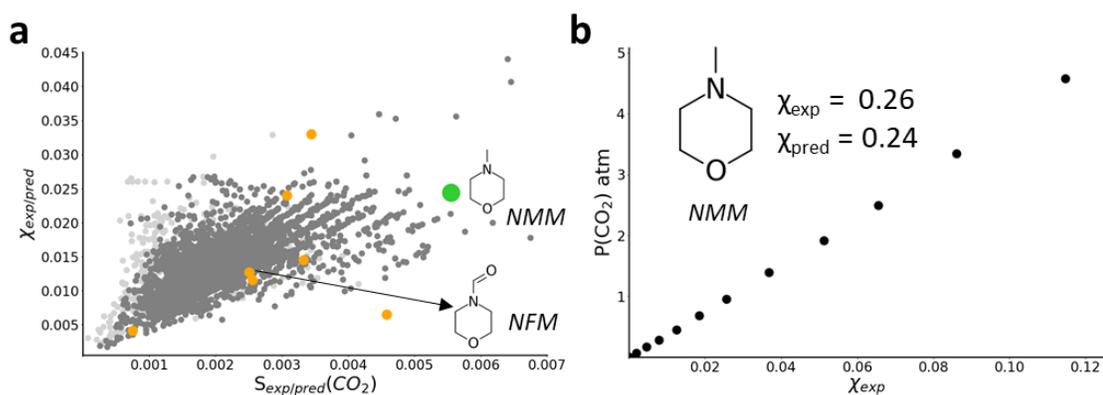
409 *Virtual screening*

410 To find new solvents with high CO₂ solubility and high selectivity towards other gases, we
411 performed the virtual screening of the in-house library of industrially produced chemicals and
412 their close structural analogs comprising more than 4,000 chemicals (Figure S9). It is worth
413 noting that the experimentally measured physico-chemical properties such as melting and boiling
414 points, density, flash points, etc. were available only for a small fraction of the dataset and thus,
415 we did not check if the compounds possess plausible values of properties at 298.15 K and 1 atm.
416 Most of the screened compounds (87%) appeared to be inside AD of the CO₂ model. There were

417 numerous compounds found with high predicted CO₂ mole fractions values and Kuenen
418 coefficients, several of which were superior to the existing industrially used solvents (Figure 3a).
419 Among the best CO₂ solvents according to mole fraction solubilities were tertiary amines and
420 long-chain esters (e.g., dioctyl adipate, $\chi_{\text{pred}} = 0.27$), while the largest Kuenen coefficients were
421 for tertiary amines and the close structural analogs of the compounds with the largest Kuenen
422 coefficients from the learning set: ethers (e.g. ethyl methyl ether, $S_{\text{pred}} = 0.0068$), ketones (e.g.
423 methoxyacetone, $S_{\text{pred}} = 0.0053$) and nitriles (e.g. butyronitrile, $S_{\text{pred}} = 0.0052$). One of the
424 tertiary amines with the largest Kuenen coefficient ($S_{\text{pred}} = 0.0054$) – 4-Methylmorpholine
425 (NMM) was selected for the experimental measurement of solubility. NMM showed linear
426 variation of mole fraction solubility vs partial pressure of the gas in the pressure range indicating
427 pure physical solubility (Figure 3b). The experimental mole fraction solubility (0.26) matched
428 the predicted one (0.24) well. The CO₂ solubility in NMM is appreciably higher than in
429 industrially used NFM, which instead of a tertiary amine group contains an amide group. We
430 have measured the dynamic viscosity of NMM: 0,92 cP at 20 °C. The dynamic viscosity of water
431 at 20 °C is 1 cP. The viscosity of NMM is thus comparable to water. NMM is much less viscous
432 than e.g. pure MDEA (100 cP at 20 °C) or pure EDEA (90 cP at 20 °C), which is a significant
433 advantage. On the other hand, the boiling point of NMM is 116 °C (MDEA 243 °C). NMM is
434 thus more volatile than MDEA. The NMM solvent should thus be used at a lower temperature, to
435 minimize the solvent losses. This is e.g. also done in the Rectisol process which uses methanol
436 (boiling point 65 °C).

437 The environment, health and safety (EHS) of solvents for CO₂ capture is a potential issue. In
438 principle, amine emissions should not be an obstacle because the causes are well known and
439 counter-measures can be put in place (operating temperature and pressure, water wash, Brownian

440 demister, reclaiming units, etc.). One clear advantage of using physical solvents is that there is
 441 much less thermal and oxidative solvent degradation because the regeneration is not thermal and
 442 the high operating pressure avoids oxygen ingress. According to the safety datasheet¹⁰⁸ NMM is
 443 flammable, corrosive and harmful, but the substance contains no components considered to be
 444 either persistent, bioaccumulative and toxic.



445
 446 Figure 3. (a) A plot of CO₂ molecular fraction values vs Kuenen coefficients. Experimental values – black and
 447 orange (solvents used in the industry). (b) Variation of mole fraction with partial pressure for CO₂ in NMM at
 448 298.15 K experimentally measured in this paper; χ_{exp} – experimental mole fraction value at 1 atm and 298.15 K, χ_{pred}
 449 – predicted value. Predicted values for compounds inside AD – grey, outside AD – light grey, for NMM – green.
 450 The position of the NFM on the plot is shown for comparison.

451
 452 The selectivity of the NMM calculated from predicted mole fraction values is comparable to
 453 the one of industrially used solvents (Figure S10). Other tertiary amines were also among the
 454 most selective solvents. For example, the 3-(Dimethylamino)-1,2-propanediol was among the
 455 most selective solvents for all gases. Among other classes of solvents with the highest selectivity

456 indexes were cyclic amides (e.g. 5-(hydroxymethyl)-1-methylpyrrolidin-2-one) and ketones (e.g.
457 methoxyacetone).

458 To conclude, the rational approach to the design of new physical solvents based on the usage
459 of machine learning for modeling of structure-solubility relationships was suggested in this
460 paper. The collected data on solubility of gases were used to build QSPR models, which were
461 then applied to identify compounds potentially superior to the existing ones via virtual screening
462 of industrially produced chemicals. We have identified pure tertiary amines with a remarkable
463 CO₂ absorption capacity. Previously, the team of Heldebrandt et al.¹⁰¹ has investigated the use of
464 pure, anhydrous amines for high pressure CO₂ absorption. They compared the performance of
465 anhydrous EDEA to the Fluor solvent (propylene carbonate), to Selexol, and to aqueous MDEA
466 for a representative absorber. Despite the attractiveness due to lower energy consumptions, the
467 use of anhydrous or water-lean amines faces numerous challenges, for example, their lower
468 absorption capacity and their higher viscosity.⁶ In this work we have focused on the gas
469 solubility. A further extension of the chemoinformatics workflow for the prediction of other
470 industrial important solvent properties might be very useful in the identification of the most
471 suitable physical (co-)solvent (optimal absorption properties, selectivity, viscosity,¹⁰⁹ EHS
472 impact,¹¹⁰ etc.) for a given application.

473

474 ASSOCIATED CONTENT

475 **Supporting Information.**

476

477 Table S1. Mole fraction solubilities of gases in organic liquid solvents at 298.15 K and 1 atm.

478 Figure S1. Negative logarithm of mole fraction solubility values distribution.

479 Figure S2. A scheme for building the ISIDA consensus model.

480 Text S1. Description of the experimental protocols.

481 Figure S3a. Schematic diagram of apparatus used to determine gas solubility.

482 Figure S3b. Flow diagram of the synthetic apparatus used to determine gas solubility.

483 Figure S4. A pictorial view of CO₂ loading arrangement.

484 Figure S5. Plots of experimental molecular fraction values vs Kuenen coefficients for (CH₄, H₂,
485 CO, N₂).

486 Figure S6. Plots of selectivity indexes based on experimental molecular fraction values vs CO₂
487 Kuenen coefficients.

488 Table S2. Outliers from ISIDA consensus models.

489 Table S3. Performance estimation for modeling using quantum-chemical descriptors.

490 Figure S7. Variation of CO₂ solubility in several series of structurally similar solvents.

491 Figure S8. Learning curves for machine learning models. Figure S9. Distribution of molecular
492 descriptors for the compounds from the screening library and the learning set.

493 Figure S10. Plots of predicted selectivity indexes vs Kuenen coefficient of CO₂.

494

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503 **Author Contributions**

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514 ABBREVIATIONS

- 515 Caroxin D – 1,1,2,2,3,3,4,4-octafluoro-1,4-bis(1,1,1,2,3,3,3-heptafluoropropan-2-yloxy)butane
- 516 Caroxin F – 1,1,1,2,2,3,3,4,4,5,5,6,6-tridecafluoro-6-(1,1,1,2,3,3,3-heptafluoropropan-2-yloxy)hexane
- 517
- 518 DEG – 2-(2-hydroxyethoxy)ethanol (diethylene glycol)
- 519 DEGM – 2-(2-Methoxyethoxy)ethan-1-ol (diethylene glycol monomethyl ether)
- 520 diglyme – 1-methoxy-2-(2-methoxyethoxy)ethane
- 521 DMF – N,N-dimethylformamide
- 522 DMI – 1,3-Dimethylimidazolidin-2-one
- 523 DMSO – methylsulfinylmethane (dimethyl sulfoxide)
- 524 EG – ethane-1,2-diol (ethylene glycol)
- 525 glycerol – propane-1,2,3-triol
- 526 HMPA – N-[bis(dimethylamino)phosphoryl]-N-methylmethanamine (hexametapol)
- 527 M2CA – methyl 2-cyanoacetate
- 528 MDEA – 2-[2-hydroxyethyl(methyl)amino]ethanol 2-[ethyl(2-hydroxyethyl)amino]ethanol
- 529 EDEA – 2-[ethyl(2-hydroxyethyl)amino]ethanol
- 530 DEAE-EO – 2-[2-(diethylamino)ethoxy]ethanol
- 531 methoxyacetone – 1-methoxypropan-2-one
- 532 NMM – 4-methylmorpholine

- 533 NFM – morpholine-4-carbaldehyde (N-formylmorpholine)
- 534 NMP – 1-methylpyrrolidin-2-one
- 535 PC – 4-methyl-1,3-dioxolan-2-one (propylene carbonate)
- 536 TDG – 2-(2-hydroxyethylsulfanyl)ethanol (thiodiglycol)
- 537 pentaglyme – 1-methoxy-2-[2-[2-[2-(2-methoxyethoxy)ethoxy]ethoxy]ethoxy]ethane
- 538 perflubron – 1-bromo-1,1,2,2,3,3,4,4,5,5,6,6,7,7,8,8,8-heptafluorooctane
- 539 perfluoroheptane – 1,1,1,2,2,3,3,4,4,5,5,6,6,7,7,7-hexafluoroheptane
- 540 perfluoro(methylcyclohexane) – 1,1,2,2,3,3,4,4,5,5,6-undecafluoro-6-
- 541 (trifluoromethyl)cyclohexane
- 542 perfluorooctane – 1,1,1,2,2,3,3,4,4,5,5,6,6,7,7,8,8,8-octafluorooctane
- 543 perfluorotributylamine – 1,1,2,2,3,3,4,4,4-nonafluoro-N,N-bis(1,1,2,2,3,3,4,4,4-
- 544 nonafluorobutyl)butan-1-amine
- 545 THF – oxolane (tetrahydrofuran)
- 546 TPrP – tripropyl phosphate
- 547 χ – mole fraction solubility
- 548 S – Kuenen coefficient
- 549 SI – Kuenen coefficients selectivity index
- 550 squalane – 2,6,10,15,19,23-hexamethyltetracosane

551

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