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Augmenting the Communication and Engagement Toolkit for CO_2 Capture and Storage Projects

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A B S T R A C T

This paper revisits the Communication and Engagement Toolkit for CO_2 Capture and Storage (CCS) projects proposed by Ashworth and colleagues in collaboration with the Global CCS Institute. The paper proposes a new method for understanding the social context where CCS will be deployed based on the toolkit. In practice, the proposed method can be used to harness social data collected on the CCS project. The outcome of this application is a development of a predictive tool for gaining insight into the future, to guide strategic decisions that may enhance deployment. Methodologically, the proposed predictive tool is an artificial intelligence (AI) tool. It uses fuzzy deep neural network to develop computational ability to reason about the social behavior. The hybridization of fuzzy logic and deep neural network algorithms make the predictive tool an explainable AI system. It means that the prediction of the algorithm is interpretable using fuzzy logical rules. The practical feasibility of the proposed system has been demonstrated using an experimental sample of 198 volunteers. Their perceptions, emotions and sentiments were tested using a standard questionnaire from the literature, on a hypothetical CCS project based on 26 predictors. The generalizability of the algorithm to predict future reactions was tested on, 84 out-of-sample respondents. In the simulation experiment, we observed an approximately 90% performance. This performance was measured when the algorithm's predictions were compared to the self- reported reactions of the out of sample subjects. The implication of the proposed tool to enhance the predictive power of the conventional CCS Communication and Engagement tool is discussed

1. Introduction

Carbon capture and storage (CCS) has emerged as a potential solution in the global efforts toward achieving the ambitious target in the Paris agreement to fight climate change. However, social acceptance of the technology has emerged as a problem. To secure a long-term social license for CCS projects, the need to understand the social context in which the technology will be deployed is a

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necessary part of the CCS Communication and Engagement process. To provide practitioners with practice-based tools, Ashworth and colleagues, in collaboration with the Global CCS Institute, proposed the Communication and Engagement Toolkit for CCS projects (Ashworth et al., 2011: https://www.globalccsinstitute.com/resources/publications-reports-research/communication-engagement-toolkit-for-ccs-projects/). This practitioner-based toolkit was developed using insights from the literature and focusing on five cases: the Barendrecht, FutureGen, Carson, Otways, and ZeroGen projects. It also underwent peer review and feedback from a series of global workshops, which shaped its current content. According to the authors, this theoretically driven but practice-oriented tool "has been designed as a universal guide for implementers and developers of CCS projects. It is intended to be a practical and informative tool to assist in the design and management of communication and engagement activities for individual CCS projects." (Ashworth et al., 2011, p.2). This work was published a few years ago, but to the best of our knowledge it is the only work in the literature that provides a comprehensive guide for developing CCS projects, making it worthwhile to revisit.

The content of the toolkit is grouped into four sections: social data collection, a SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis, preparing a stakeholder analysis, and developing a high-level public engagement plan. In this present work, our focus is on the SWOT strategic tool and the purpose it is recommended for. Its purpose is to exploit the social data on CCS to make predictions to guide decision-making. For example, in the toolkit, it is stated that the SWOT "could be performed after the qualitative and quantitative data has been collected, giving the developers a better ability to make recommendations and predictions based on un-biased, factual evidence" (Ashworth et al., 2011, p.34). In the present study, we have appraised this novel work within the broader context of the science of prediction (Breiman, 2001; Shmueli, 2010) and the role of SWOT and discovered a few limitations. We find that the environment in which the project developers will operate is volatile and full of uncertainties. The SWOT strategic tool recommended in the toolkit for project managers in accomplishing the task of predictions is ill-suited for such purposes (see discussion section for more).

To overcome the limitation, the goal of this present study is to add value to the toolkit by proposing an alternative solution based on Artificial Intelligence (AI) technique. Taking this AI approach, in this paper, an AI powered predictive tool based on the toolkit is proposed. Methodologically, this artificial intelligence based approach uses fuzzy deep learning incorporated with a Likert scaling strategy, for capturing opinions and reasons without information distortion (Symeonaki & Kazani., 2011; Li, 2013). Deep learning algorithms use neural networks, popularly known as deep neural networks (DNN) to mimic the human brain function at an abstract level (LeCun, Bengio, & Hinton, 2015; Deng & Yu, 2014; Goodfellow, Bengio & Courville, 2016; Deng et al, 2016; Deng et al., 2017). Deep learning helps human experts to work with advance based computer algorithms to train computers to do what comes naturally to humans; learn by examples where examples is data and data can be sound, image and language. In the context of this study, data is social data on the CCS project. This social data is the qualitative and quantitative information obtained from the social participants who have direct and indirect stake on the CCS project (e.g. citizens and local authorities). Depending on the social behavior under observation, the social data can either be categorical or numerical or both. In page 3 of the toolkit, Ashworth and colleagues state that "the aim of the gathering social data is to learn and understand about the consequences of the proposed CCS project on the population and community.” This social data is a high dimensional data with many attributes, and the deep neural network can model complex structure in this type of data and produces accurate predictions. The limitation however is that: the algorithm’s decision is challenging to interpret due to its blackbox nature. One approach to overcome this limitation in traditional deep learning using neural network is to incorporate fuzzy logical thinking into the computational process. The combination leads to a deep learning architecture called fuzzy deep learning (also known as fuzzy deep neural network). The fuzzy deep learning architecture makes it possible to model with natural languages so that it becomes easy to interpret the computational process using fuzzy mathematics (Bonanno et al., 2017). This fuzzy logic mathematics expresses an if..then rule inference such that if we know a fact (premise, hypothesis, antecedent), then we can infer or derive another fact, called a conclusion (Ross, 2010). In the field of machine learning, this interpretable approach to machine learning is called explainable AI system (for more review see Rudin,2019). This explainable AI technique is the approach adopted in the system modeling of the proposed AI tool for CCS projects, to augment the SWOT approach in the toolkit to infer accurate predictions

The work is organized as follows. In *Section* 2, the theoretical framework of the proposed AI tool based on the toolkit is presented. The framework will be explained in the context of a modified SWOT framework adapted from the toolkit. It is to help the reader to understand the strengths and limitations of the toolkit, and where the proposed AI system adds value. In *Section 3*, a demonstration of how the system can be applied to social data is presented using a hypothetical CCS project. The results of the simulation experiment are also presented in this section. Following the result is the implication of the work on the toolkit. The implication of the work on theory and practice is discussed in *Section 4* with a concluding remark, limitations and future studies.

2 Theoretical framework of the proposed AI tool based on the toolkit

Fig. 1 presents the framework of the proposed AI algorithm for enhancing the SWOT capability in the toolkit for quantitative predictions.

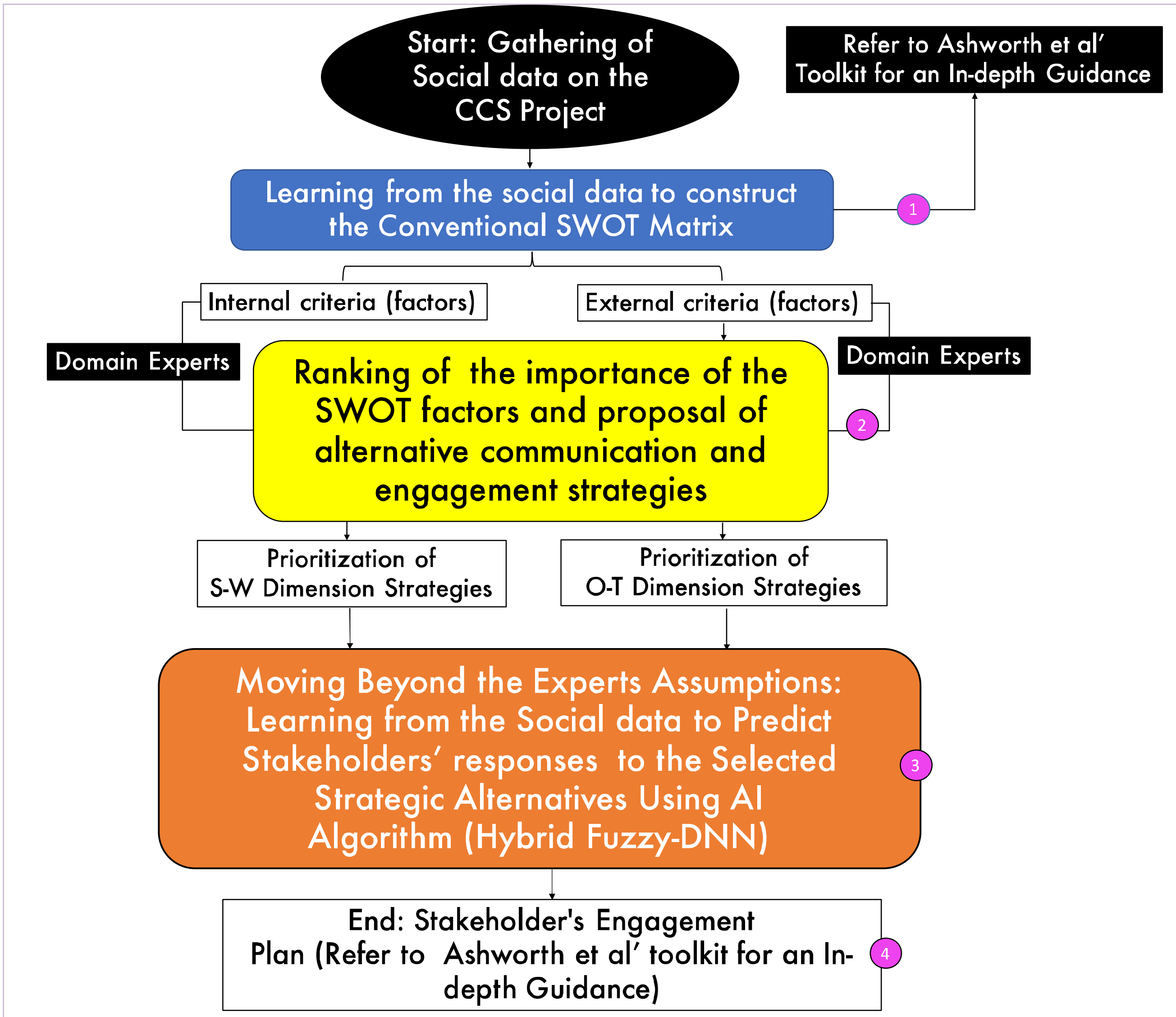

Fig. 1. The framework of the proposed solution for enhancing the SWOT strategic component proposed in the toolkit

As Fig. 1 illustrates, the proposed method does not disregard the knowledge in the toolkit. It builds on its strengths to make it robust. As indicated in the framework, to use the proposed method, the project experts need to go through four (4) processes. The first process is the same as proposed in the toolkit: gathering and learning from the social data to construct the conventional SWOT matrix, and further use it to gain insights into the project's external environment. In the toolkit, Ashworth and colleagues provide an in-depth guide-sheet on how to do carry out this task. They also suggest some of the questions to ask in order to gather the social data, which we recommend be used.

The second process is engaging the project experts to rank the importance of the SWOT factors so as to prioritize them. As indicated in the toolkit, at this stage we have the SWOT factors finalized, and the project expert can propose alternative communication and engagement strategies. For example, on page

34 of the toolkit, there is an example of how a CCS SWOT of a stakeholder "media group" might look, as shown in the modified version in Fig. 2.

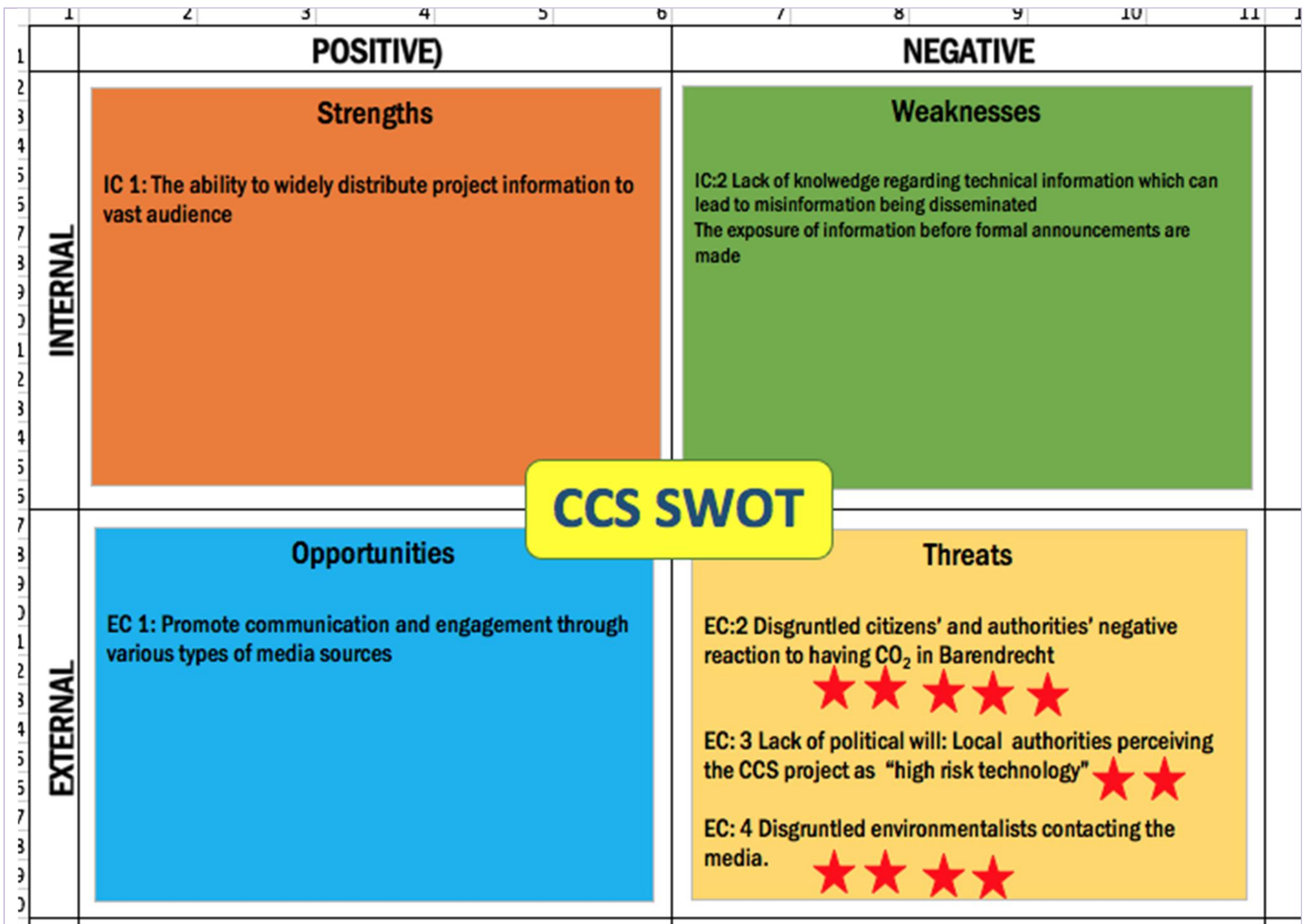

Fig. 2. An example of a CCS SWOT matrix (modification adapted from Ashworth et al., 2011, p.34). The "stars" indicate the experts' evaluation of the importance of the SWOT factor. In its original form, there are no "stars" and "Disgruntled environmentalists contacting the media" was the only threat factor in the SWOT Matrix. The modification has been done for the purpose of explanation.

In this example SWOT, consider an external criterion whereby *"disgruntled environmentalists contact print and broadcast sources in regard to the project."* According to Ashworth et al. (2011), "a strategy to minimize this threat would be to not only identify those potential disgruntled groups, but once identified, engage them through transparent communication and address any inaccurate information" (p. 34).

In a real-life project, this process could lead to several proposed strategies. Some of the key questions that may arise are:

(a) Which are the most effective strategies among the list of strategies?

(b) What will be the response of the external stakeholders on the selected strategy, especially in the external environment?

It may be either tedious or challenging for the experts to make accurate guesses on the effectiveness of one strategy in relation to another, due to their lack of understanding of the non-linear dependencies among the factors in the CCS SWOT. Since the reaction of their external stakeholders to a selected strategy in relation to a SWOT criterion is beyond the influence of the project expert, they can just make a qualitative prediction of the likely responses. However, the human mind and emotions change in every waking moment as we interact with our social world, which makes our future actions uncertain (Wilson & Gilbert, 2003; Barrett, 2017). Due to our knowledge deficit regarding the future, Wilson and Gilbert state that it is challenging for us to even predict our own future feelings (Wilson & Gilbert, 2003). One approach to overcoming this challenge is affective forecasting based on affective computing. In this approach, Artificial Intelligence algorithms are used to model and learn from sample data to develop the capability to predict the future accurately. Using this technique, in the context of a CCS project, Lotfi A. Zadeh, the father of Fuzzy mathematics and Fuzzy Logic (Zadeh, 1965; Zadeh, 1975; Zadeh, 2002) notes that the project experts' imprecise reasoning about the observed situation in the qualitative SWOT, for example, provides valuable information for initiating the training of the intelligent machines. Drawing inspiration from this technique, as indicated in the framework in Fig.1, our value-adding to the toolkit adds one more step to the second process (step 3). This step uses machine learning capability to perform the probability task of the future. It uses an artificial intelligence technique called "hybrid fuzzy-deep neural network" to harness the SWOT criteria. How it works in practice is presented in the next section.

2.1 Architecture of the AI framework and the basic mathematics behind

In reference to page 34 of the toolkit, let us assume a CCS SWOT matrix as illustrated in Fig. 2.

Using this modified CCS SWOT case (Fig. 2), let us assume a scenario in the SWOT analysis where the project experts have already ranked the external criterion (EC:2): "*Disgruntled local citizens' and authorities' negative reaction to having CO_2 storage in Barendrecht*" as an important threat criterion, likely to occur in the external environment.

In real life, a strategy that could be used to mitigate or manage this threat might be to engage the local citizens and authorities of Barendrecht in an emotional debate using deliberative engagement and public consultation strategies (Roeser, 2011; Coyle, 2016). This approach can be effective; however, there are challenges associated with this communication and engagement strategy including social desirability bias. For example, social desirability bias makes people to be dishonest with their true feelings at the face-to-face workshop but may leverage it to support collective actions against the project (Avelino (2009; Avelino, 2017) (see discussion section for more). This is where it becomes necessary for the project experts to move beyond their assumptions about what the community thinks initially and consider what they will think in the future. Its due to the nature of the social license granted to CCS project, and it is supported by Gough et al. (2018) (see discussion). How the system processes the EC:2 SWOT criteria to predict the future behaviors and social license concerning the CO_2 project in the candidate city is shown in the system architecture in Fig. 3.

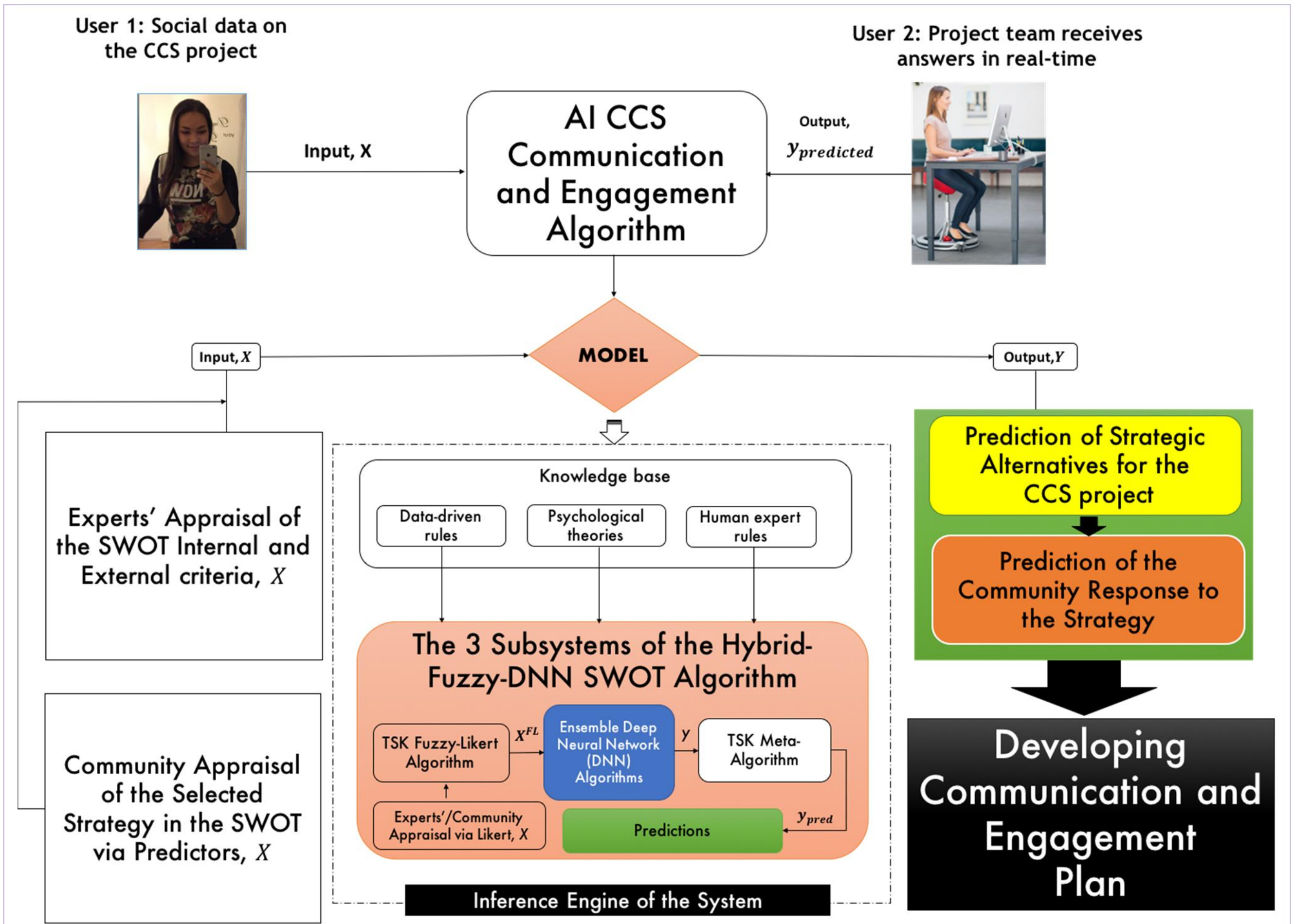

Fig. 3. Architecture of the proposed Artificial Intelligence algorithm for modeling expert opinions and social data on CCS projects to predict best strategic alternatives (communication and engagement strategies) and community response to the selected strategy

As illustrated in the algorithmic framework in Fig. 3, the system processes this information by using the hybrid fuzzy-deep neural network technique explained in the introduction. Within this hybrid-fuzzy deep learning framework, it makes its final decisions using the contributions of three subsystems (TSK Fuzzy-Likert classifier + Ensemble DNN Algorithm + TSK Meta algorithm) that make up the system. How these three subsystems exchange information and arrive at a decision mimics how the biological neural system in the human body works, as illustrated in Fig. 4.

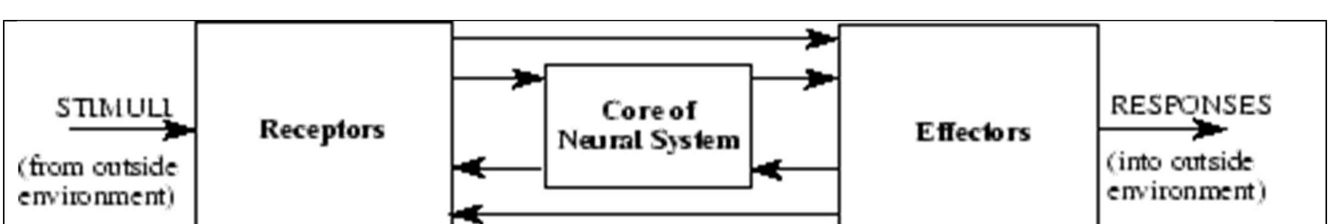

Fig. 4. Illustration of the three subsystems of the biological neural system

As depicted in Fig. 4, the biological neural system has three subsystems: receptors, a neural network, and effectors. The receptors receive the stimuli either internally or from the external world, then pass the information to the neurons in the form of electrical impulses. The neural network then processes the inputs and decides on the appropriate outputs. Finally, the effectors translate the electrical impulses from the neural network into responses to the outside environment (Arbib, 1987). Drawing inspiration from this biological counterpart, in the system architecture, the first subsystem (TSK Fuzzy-Likert Classifier) mimics the behavior of the biological receptors. The second subsystem (ensemble deep neural network, DNN algorithm) mimics the behavior of the biological neurons using the artificial neurons of multiple neural networks, called deep learning. Finally, the final subsystem (TSK Fuzzy Meta algorithm) mimics the behavior of the biological effectors.

2.1.1 Data acquisition and processing by the first and second subsystems

Mimicking the biological counterpart in Fig.4, mathematically, as illustrated in Fig.3, when the system receives a response X either from an experts or a citizen on a SWOT criteria or social factor, the first subsystem reacts. It uses mathematics of fuzzy logic to process the numerical and linguistic information (for more review about fuzzy mathematics see Zadeh, 1965; Zadeh, 1975). In real life, X is measured on a Likert scale inline with standard social science practice in the CCS literature. However, because the distance between two ordinal responses on a Likert scale is unknown, the experts are forced to make many subjective decisions when a response falls outside the scale or not represented. Earlier studies found that this leads to inaccurate measurements due to information distortion (Symeonaki & Kazani, 2011; Li., 2013). The proposed system overcomes this limitation in the modeling process by rescaling and standardizing responses into a fuzzy scale range from 0 to 1 using a mathematical curve called membership function. Mathematically this fuzzy membership functions allow modelers to graphically represent a fuzzy set. The type of membership one choses has impacts on the system performance. There are different types of memberships function including triangular membership, trapezoidal membership and Gaussian membership. In the study, the motive of rescaling the Likert responses using the fuzzy mathematical curve is to have a continuous variables of the ordinal values on a fuzzy scale so that the intervals details are known. As highlighted above, knowing the interval details of the parameter prevent information distortion or lost (Symeonaki & Kazani.,2011). The rescaling is necessary in the framework due to the following reason. When the system is built and implemented in real life, respondents' opinions do not need to be constrain as it is usually done in Likert question because their true feelings about the CCS projects is not represented. In other words, they will not need to be force to choose an option as it in the case of Ashworth and colleagues sample question in the toolkit. In this way, they will have the flexibility to express their true feelings and assigned their own qualitative or quantitative weight about the CCS project, other than what is defined. Since human thinking is not always "black and white," but a smooth transition from "black to white", we assumed that logically, the smooth nature of Gaussian, theoretically mimics the smooth nature of human thinking pattern and it worked in the experiment. The Gaussian Member function which is given by:

$$\mu_{A^i}(x) = \exp(-\frac{(ci-x)^2}{2\sigma_i^2}) \qquad (I)$$

where ci and σi are the centre and width of the ith fuzzy set Ai, respectively.

Using this fuzzy mathematical reasoning, as indicated in the system architecture in Fig.3, the Likert responses, X receive by the first subsystem are then transformed and re-scaled to obtain it fuzzy representatives where their distances are known. This fuzzy logic based Likert responses or features is labeled X^{FL} in the framework.

To demonstrate the behavior of this first subsystem in the framework using Gaussian membership, consider a case called *Trust in information sources* in Ashworth et al (2011) work in page 15 to 18. In this case in the toolkit, Ashworth and colleagues provided an example guide sheet for the person or group responsible for collecting the social data. In page 16 of the toolkit, the question was "*"How much do you trust the following information sources?"* The community stakeholders are expected to response to a 7- point Likert scale where 1 represents *"Strongly distrust"* and 7 represents *"Strongly trust"*. When the community stakeholder responds to the question, the $X\ information$ is pre-processed by the first subsystem using the fuzzy logic technique. The technique uses a fuzzy rule inference engine. The rule that is used to design this Fuzzy Likert inference engine could be defined by human experts. The goal is just to give the algorithm a hint of the problem under study to understand the structure in which the data will be collected from the participants. For example, will the participants expressed their thought on 5-level scale or 7-level scale etc.? An example of a 5-level rules is used in in the simulation experiment in *Section 3.3 Table 3*. The rule inference is also constructed using the membership curve to mathematically convert the X values into its fuzzy values. For the purpose of this demonstration, 7-level Gaussian membership function is used shown in Fig. 5. 7-level membership function simply means that the participants will express their thought on 7-level Likert scale as it is the case with *Trust in information sources* in Ashworth et al toolkit.

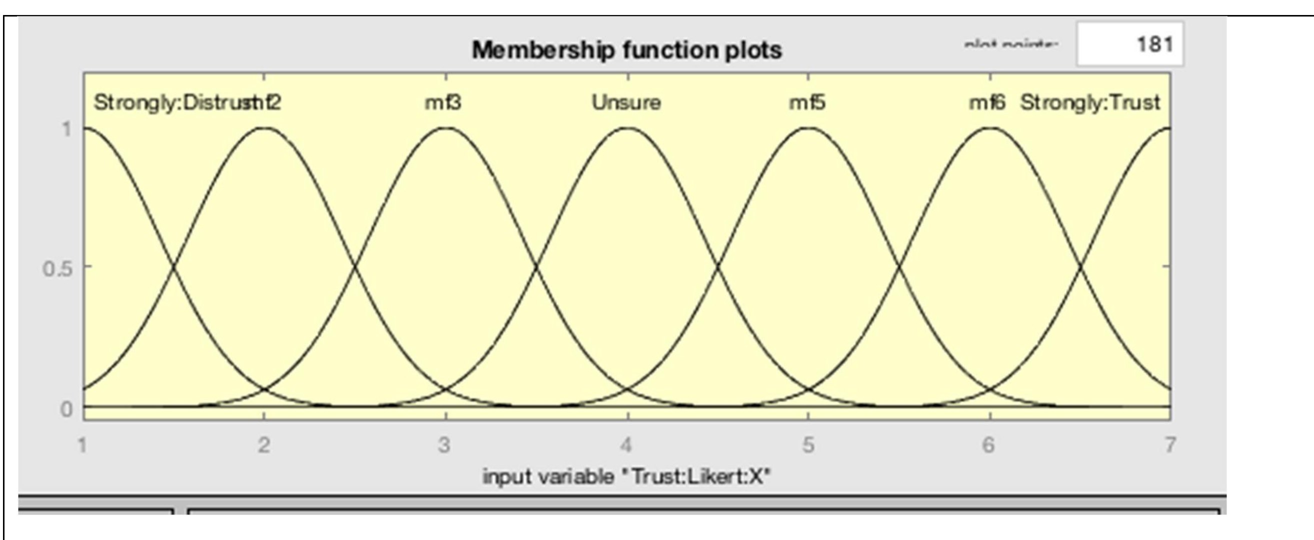

Fig. 5 Illustration of a simulation model of how to quantify a respondent qualitative response on Likert to Fuzzy Likert, and assigned a numerical weight using a mathematical curve called Gaussian membership function (MF).

Using this 7-level membership information, the following human-level rules in Table 1 can be use to construct the inference engine for the first subsystem.

Table 1
Fuzzy rules for the $\boldsymbol{X}$ and $\boldsymbol{X^F}$ mappings

Fuzzy Rules	Input, X		Output, X^F	
	IF (*Trust in Information source is….*)	Weight of responses on Likert [1-7]	THEN….(*Its Corresponding Fuzzy Likert is…*)	Weight of response on Fuzzy Likert Scale [0,1]
Rule 1	MF 7: *Strongly trusted by the community*	7	MF 7: *Strongly trusted by the community*	1
Rule 2	MF 6: *Reasonably much trust*	6	MF 6: *Reasonably much* trust	0.833
Rule 3	MF 5: *Much trust*	5	MF 5: *Much trust*	0.6667
Rule 4	MF 4: *Moderately trusted*	4	MF 4: *Moderately trusted*	0.5
Rule 5	MF:3 *A bit of trust*	3	MF:3 *A bit of trust*	0.333
Rule 6	MF 2: *A little bit of trust*	2	MF 2: *A little bit of trust*	0.1667
Rule 7	MF 1:*Strongly Distrust*	1	MF 1:*Strongly Distrust*	0

With the understanding from the demonstration, the X to X^{FL} transformation also comes with an added advantage. It creates a high dimensional data space on X^{FL}. Using the technique of data augmentation, additional data can be collected on the high dimensional data space of X^{FL} to train the second subsystem in the framework called ensemble deep neural network. For more review about this data augmentation technique see the work of Buah et al, (2020) and Shorten & Khoshgoftaar (2019).

In practice, unlike the first subsystem can be implemented using fuzzy logic toolbox in Matlab, the second subsystem is advance algorithm. It can be implemented using for example, Keras machine learning library with Google TensorFlow backend. In the computational process, the second subsystem is responsible for making the higher-level decision on the behavior under observation. It is similar to how the neurons in our brains in the biological system are responsible for making decision after receiving information from the receptors. Mimicking these neurons in our brain, as illustrated in Fig. 6, during the decision making, the hypothesis defining the non-linear relationship between the responses and an intended outcome is learnt using a technique called supervised learning.

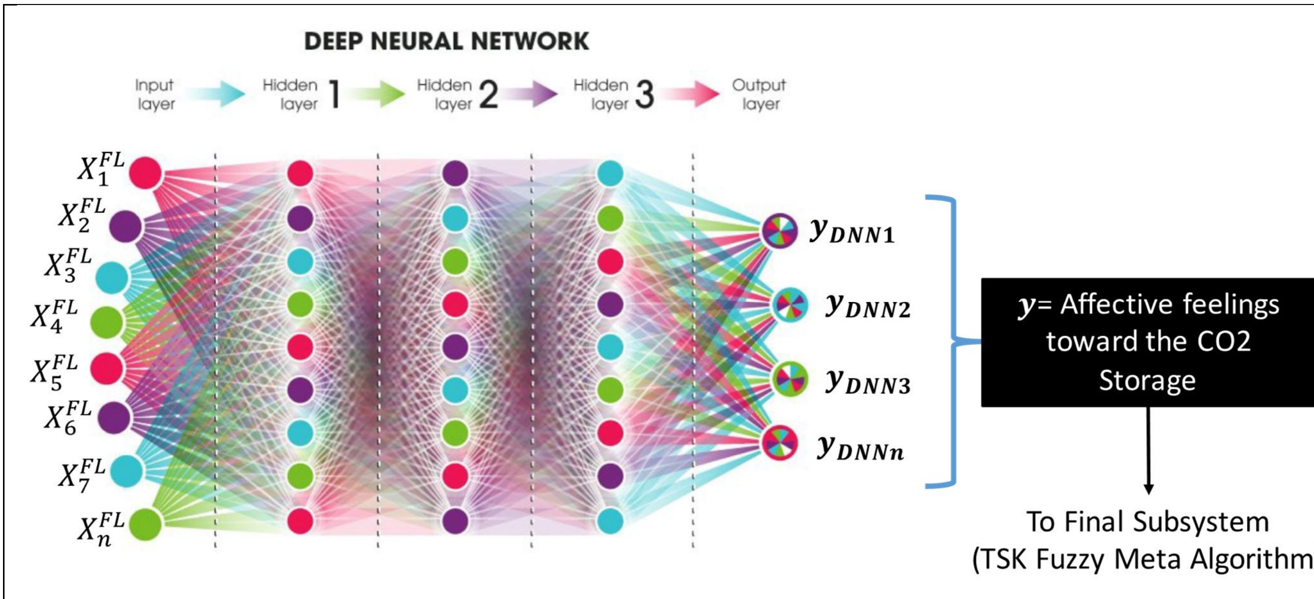

Fig.6. How the ensemble fuzzy-deep neural network algorithm learns the relationship mappings by mimicking the biological neurons in the human brain, using artificial neurons

In supervised machine learning, the machine is trained using sample data (called training data), which is well "labeled." This means that some data is already tagged with the correct answer in the sample data at hand. It can be related to learning that takes place in the presence of a supervisor or a teacher. It is an opposite form to the linear regression and causal modeling style. In this technique, we do not fit a pre-defined hypothesis to the real data but instead the hypothesis is constructed from the natural structure of the raw data. The goal is not model fit but appropriate fit, since to fit is to overfit and overfitting occurs if there is high variance in the machine learning. Overfitting makes models to be sensitive to the data environment and leads to poor generalization. When this happens, the fitted model can perform excellently on the real-life data used for the model fitting, only to be tested with out-of-sample data (test data) and perform poorly (Breiman, 2001; Shmeuli, 2010; Yarkoni &Westfall, 2017).

Using this supervised technique, as illustrated in Fig. 6, the second subsystem takes the pre-processed X^{FL} features as its input data. Mathematically, assuming we are modeling to predict reaction to the CO_2 Storage in Barendrecht in the SWOT matrix in Fig.2. During the learning and optimization, a non-linear function will be applied to X^{FL} and multiplied by an appropriate weight function, w, and then summed up. The result is recalculated by an activation function, f plus a bias (+1). The output decision is then expressed in equation 2:

$$Reaction\ to\ the\ CO2\ storage\ in\ Barendrecht\ \ y = f(\textstyle\sum_{i=1}^{P} X^{FL}{}_1 W_1 + bias) \qquad (2)$$

In plain language, in equation 2, all what the algorithm is attempting to do is to model the responses as weight signals using a group of neural networks called deep neural networks as shown in Fig. 6. As a non-linear model, during the training, it models the non-linear dependencies in the data being used for the training to develop its foresight of the future with little intervention from humans. It is a complex and dynamic system, and it builds the general hypothesis to observe the future out of simpler ones to form a graph of hierarchies. A graph of these hierarchies consists of many artificial neurons, which are connected by layers. In this connection, an output of one artificial neuron automatically becomes input information to another (LeCun, Bengio & Hinton, 2015; Deng & You, 2014; Goodfellow, Bengio & Courville, 2016; Deng et al., 2017). The term ensemble in the second subsystem means that in the model more than one of this complex network is used. In practice, the ensemble fuzzy-deep neural network algorithm behaves like a group of human CCS experts who bring their respective experience to the table and arrive at a decision.

2.1.2 Output decision of the system by the final subsystem: prediction

As indicated in the system architecture in Fig.6, after the second subsystem has finished making it higher-level decision, these individual decisions of the ensemble deep neural network ($y_{DNN1,}$ $y_{DNN1...,}y_{DNNn}$) are computed as, y. As demonstrated in the hypothetical case in Fig.7 with the Matlab simulation model, the final subsystem (effector algorithm) then takes y as input. Its role is to find consensus among the higher decisions, by mathematically finding their weighted average using mathematics of fuzzy logic using fuzzy IF…Then rule inference similar to the first subsystem

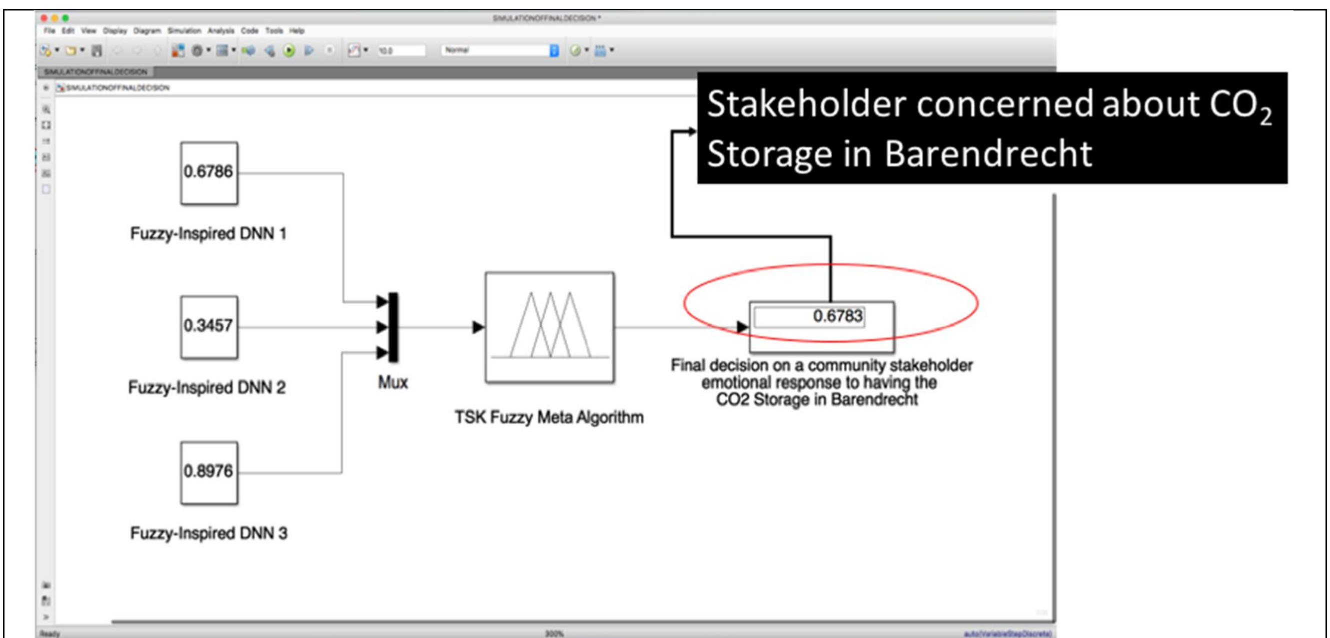

Fig. 7. An illustration of a simulation of a hypothetical case of how final subsystem receives the information from the ensemble fuzzy-deep neural network algorithm and computes the final decision.

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The decisions coming from the second subsystem are numerical in nature and are thus difficult for a non-expert to interpret. The role of the final algorithm is then to transform the decisions back to human language, similar to what the system does in using the Likert measure. The final decision is computed as $y_{predicted}$ and is communicated to the human user for further decision-making. For example, in line with Huijts et al. (2012) and Midden & Huijts (2009), the final prediction can be computed as an affective reaction using positive affect (PA) or negative affect (NA) as a measure.

3 Materials and Method

The goal of this section is to demonstrate how the framework can be applied in practice using a hypothetical case in a simulation experiment. In the experiment, we have assumed a case scenario in the SWOT matrix in Fig. 2. In this scenario, the project experts have already ranked the external criterion (EC:2) as an important threat criterion. The goal of the experiment is to applied the proposed method to the problem and develop a capability to predict the citizens' affective reactions to the CO_2 storage proposed close to them.

3.1 **Description of the dataset**

The system being proposed in this work is a machine learning system. As it was highlighted in the introduction, in machine learning, it is not strictly about population and statistics (e.g. mean, standard deviation etc.) unlike in the social sciences. Its about obtaining examples behavior of the system under observation and ensuring that it contains representative features that the algorithm can learn from. This do not suggest that the basic demographic information was not observed in the research. In this experiment, we found it necessary to have a view from respondents from developing and developed countries since their political and social structures are different. Having respondents from developed and developing countries were interesting for the study, so that the algorithm can be train with thoughts influence of different sociocultural environment. For example, to obtain the sample data, we engaged 198 volunteers (both male and females) from 15 different countries from the developed and developing countries) on a hypothetical CCS project. This observation was made using a standard questionnaire adapted from the work of Huijts et al. (2007); Midden and Huijts (2009); Xuan and Wang (2012) and Terwel et al. (2009). The respondents are heterogeneous and come from different economic backgrounds. Their professions range from unemployed to medical doctors, lawyers, university lecturers, environmentalist, teachers, PhD students, secondary school graduates and health professionals. In terms of age, we observed in our sample that the youngest respondent was 18 years and the oldest respondent was 70 years old.

3.2 **Questionnaire and Measurements**

The media used to reach these respondents were LinkedIn, Facebook, WhatsApp and Friends referral. The participants received both video and written information. This content came from both proponents and opponents' materials so that they were not exposed to one-sided information. Some of the proponents and opponents' materials used include the video content on YouTube of Scottish Power Professor of Carbon Capture & Storage, Professor Stuart Haszeldine, titled, "Fuelling the Future: Electricity with Carbon Capture and Geological Storage"; The video content on YouTube of the Zero Emissions Platform(ZEP) titled, " The Hard Facts behind Carbon Capture and Storage and the video content on YouTube of Science TV presenter and climate-change communications specialist Yasmin

Bushby, titled, "Carbon Capture & Storage'." Yasmin Bushby' material takes a neutral viewpoint in explaining CCS and its advantages and challenges in plain language to a lay audience. Greenpeace material titled "Carbon Capture Scam" was also provided to the volunteers. The YouTube video content of the carbon-capture demonstration plant, Technology Center Mongstad (TCM) in Norway, was added to give the participants a feel of how the plant might look like in real life in their local area. Since they had different materials to choose from, it limited our influence on the information shaping their attitudes and perceptions. The questions were scripted in a way that encouraged them to imagine that the project was taking place where they lived, in line with Huijts et al. (2007) and Midden and Huijts (2009). For example, instead of asking them to rate "trust in government," we said "trust in the government of my country." This was purposely done to replicate local context information.

They were observed using five psychological constructs (Trust in actors, Risk perception, Benefit perception, Reaction to Proximity, and Affective feelings toward the CO_2 storage). These five constructs are associated with 25 input predictors that, according to the literature, predict citizen responses to a CO2 storage (Midden & Huijts, 2009; Xuan & Wang, 2012; Terwel et al., 2009; Huijts et al., 2007; Huijts et al., 2012; Krause et al., 2014; Seigo et al., 2014). *Table 1 in Appendix 1* presents the predictors.

Using standard questionnaires adapted from the work of Huijts et al. (2007); Midden and Huijts (2009); Xuan and Wang (2012) and Terwel et al. (2009), the appraisal of these predictors was captured using a five-point Likert scale. For example, inline with the work of Xuan and Wang (2012), the predictors the predictors observing the participants' risks perception are shown in Table 2.

Table 2 An example of predictors observing the participants risks perception

Predictors of risks perception	*Scale of measurement (* ***5 point scale where 1/No worry at all and 5/Seriously worried about this risk case***
Sudden release of large amount of stored CO_2	1/No worry at all and 5/Seriously worried about this risk case
Bad effects on trees and plants by sudden leaked of CO_2	1/No worry at all and 5/Seriously worried about this risk case
Bad effects on human health by leaked CO_2	1/No worry at all and 5/Seriously worried about this risk case
Pipeline being destroyed by earthquake	1/No worry at all and 5/Seriously worried about this risk case
Bad effects on soil by leaked CO_2	1/No worry at all and 5/Seriously worried about this risk case
Acidification of sea water by leaked CO_2	1/No worry at all and 5/Seriously worried about this risk case
Pipeline being destroyed by corrosion	1/No worry at all and 5/Seriously worried about this risk case

The reservoir containing the CO_2 being destroyed by earthquake	1/No worry at all and 5/Seriously worried about this risk case
Overall risk perception	1/Not very risky (very small problem) and 5/ it's very risky (there will be very large problem)

As indicated in Table 1 in appendix 1, their emotions and sentiments were captured as an affective reaction in line with Posner et al. (2005); Huijts et al. (2007); Midden & Huijts (2009), and Huijts et al. (2012). Having obtained the raw data, the simulation experiment proceeded to data pre-processing.

3.3 Data pre-processing

Machine-learning algorithms use inductive inference. They learn from examples to extract a hypothesis and generalize it to unseen cases through optimization and testing. Due to this learning procedure, the 198 raw datasets, *X* were divided into training dataset and testing dataset. In machine learning, the training dataset is used for constructing the inference model. During training and validation, the data can leak to the model. The testing data is therefore used to offer objective evaluation. It is hold-on (out-of-sample) data that the algorithm has never seen before. Since algorithms are not humans, they see out-of-sample data (test data) as a future behaviour, unlike in the social sciences where separate post-test behaviour is usually required to infer the future. The test data helps in quantifying the predictive accuracy of the model to estimate its ability to generalize to unseen cases. In practice, this goes beyond model fit, which is usually used in the mainstream causal modelling economic style. In this experiment, it is about appropriate fit and predictive accuracy. In machine learning, overfitting is a high variance that leads to poor generalization of the algorithm. The predictive accuracy reveals the smartness of the agent. The higher the predictive accuracy, the better the performance that the model can predict beyond its data environment (Breiman, 2001; Shmueli, 2010; Yarkoni & Westfall, 2017). To achieve this goal, the 198 raw data was randomly divided into training data and testing dataset using the 60/40 rule. This split should have led to a 118.8 dataset for training and 79.2 dataset for testing, but a subjective decision was made. This subjective decision rounds up the decimal split and leads to a 114 (raw training data) and 84 (raw testing data) split. This decision was made to ensure that the training dataset was not dominated by, for example, responses from the participants from the developed or developing world. If this is not managed in the data pre-processing, it will increase the chance of the model becoming biased since it might learn one-sided information.

The data was then pre-processed. All missing information was filled with the global constant, "I don't know." Having acquired these values after pre-processing, the receptor algorithm (TSK Fuzzy Likert Inference Systems) was applied to the raw dataset. Five (5) Fuzzy IF...THEN rules were defined as human-level rules to initiate the learning of the receptor algorithm, as shown in Table 3

Table 3

Sample Fuzzy rules used in the experiment to transform the original data X on a Likert scale to its corresponding Fuzzy Likert features, X^{FL}			
Rules	IF ... X	THEN… X^{FL}	Fuzzy scale range of X^{FL} on a 5-level membership function, $\mu_{(x)}$
Rule 1	LOW	LOW	0 to 0.134
Rule 2	SOMEHOW LOW	SOMEHOW LOW	0.134 to 0.44
Rule 3	MEDIUM	MEDIUM	0.44 to 0.644
Rule 4	SOMEHOW HIGH	SOMEHOW HIGH	0.644 to 0.9444
Rule 5	HIGH	HIGH	0.944 to 1

In the modelling Gaussian membership was used for the experiment (refer to 2.1.1). The Gaussian membership function helped to obtain the corresponding Fuzzy-Likert features, X^{FL}. The 114 would have led to overfitting when used to train the second subsystem (DNN) because it is a complex algorithm. If the model overfits, it can perform excellently on the validation dataset as part of the training, but when it is tested with the test data it can lead to poor generalization. To prevent this, data augmentation was performed on the high-dimensional data space of the X^{FL} labels of the 114 training data. Through this data augmentation, a large experimental dataset of 72,105 training samples was collected. As illustrated in Fig. 3 (also see Fig.6) in the article, this augmented dataset was then used to train three deep neural networks.

3.4 Training, Validation and Results

The training was implemented using Fuzzy logic tools in MATLAB the Keras machine-learning library with Google TensorFlow back-end. Table 4 is the architecture of the ensemble deep neural network algorithm. That of the receptor and effector algorithm and is presented as supplementary information

Table 4 Experimental setting and system architecture	
Learner type	Neural networks
Number of output nodes	3 classes (PA, NA and MOD)
Loss function	Categorical cross-entropy
Hidden layer	Model 1 is 12-Layer network (including input and output layer, Model 1); Model 2 is 11-layer network and Model 3 had 10 hidden layers.
Training iterations	200 epochs

Learning rate	0.003
Regularization	Dropout
Activation function	Rectified linear unit (ReLU)
Optimization Algorithm	Stochastic gradient descent

As indicated in the experimental setting, the 3 ensemble DNN algorithms models were built with different hidden layers. To prevent overfitting, we introduced dropout in the architecture as indicated in Table 3 (for review about Dropout, see Srivastava et al., 2014). Using this experimental setting, we built three deep models to predict an affective reaction to CO2 storage. To objectively evaluate the model, the 84 out-of-sample data (test data) were presented to the ensemble trained models. The models' decisions were then used as input to the final sub-system (effector algorithm) as illustrated in Fig.6 . Similar to the first subsystem, the effector algorithm was implemented using the MATLAB Fuzzy logic toolbox. As shown in Table 4, the expected output is structured within the three clusters (Positive affect, PA, Negative affect, NA and Moderate affect, MOD). The predictions of the algorithm were then compared to the self-reported affective feelings of the 84 volunteers (test data). Table 5 presents the simulation results on the test data.

Table 5 Result (predictions) from the final sub-system based on the decision of the second sub-system

Decisive cases (PA and NA reactions)		Indecisive cases (MOD)	
Number of cases: 76		Number of cases: 8	
Correct	Wrong	Correct	Wrong
70 cases	6 cases	6 cases	2 cases
Overall performance on the 84 unseen cases		The algorithm predicted 76 correctly with 8 mistakes, amounting to 9.523% error with approximately 90.476% predictive accuracy.	

As indicated in the result in Table 5, after running the simulation, the algorithm was able to automatically predict the affective reaction of 76 correctly with 8 mistakes, amounting to 9.523% error with approximately 90.476% predictive accuracy. With this predictive accuracy, their overall reactions were quantified to understand influential variables and an estimate of their collective reaction and it impacts on the CO_2 storage. Fig. 8 presents the overall affective responses of the community to having the CO2 Storage facility near their homes.

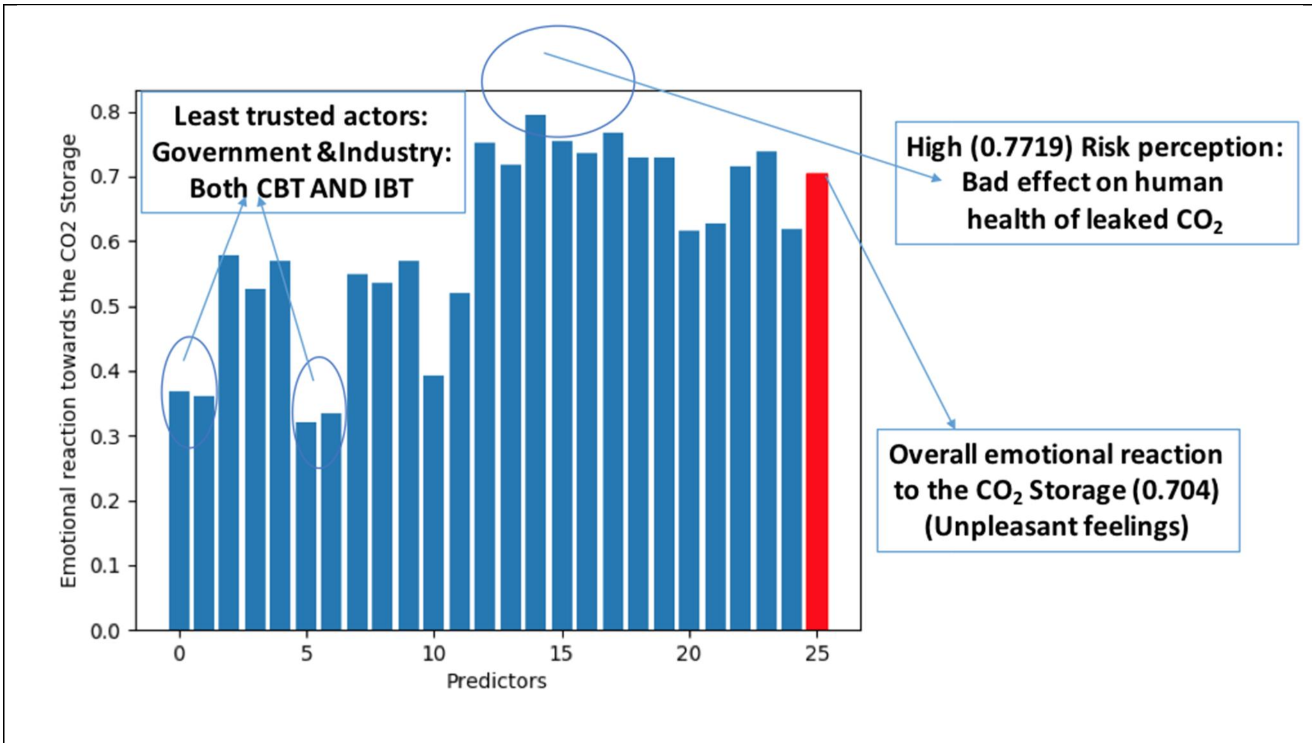

Fig. 8 Visualization of the overall affective reaction of the experimental sample and key influential variables

As indicated in the graph in Fig. 7, the algorithm is suggesting that in the observed test sample, the trust variable is one of the influential factors to the overall reaction of the imaginary community. The people have little trust in the integrity and competence of the actors proposing the project. In the algorithm's decision, the industrial actors and the government of their countries were the least trusted. This lack of trust heightened their perceived risk of the effect of the project on the environment, their own safety, and the safety of those they care for, such as family members and their offspring. For example, it can be observed in Fig. 8 that the overall risk perception of the community towards the project of having bad effect on human health by leaked CO2, contributed the highest magnitude of 0.7719 within a fuzzy scale of 0 to 1. This fuzzy scale is approximately 77.19% on a percentage scale. This observation is consistent with prior studies (e.g see Terwel et al, 2019; Yang et al, 2016). For example, in their Chinese sample, Yang et al (2016) `s observation is consistent with the algorithm' observation that, perceived risk is among the most important indicator to acceptance of CCS project.

In line with Terwel et al (2009), the authors also observed that trust enhances expected benefits and eases concerns about the risks of CCS. According to Roeser (2011), given the situation revealed by the algorithm in the social context, if an intervention is to be given, the project actors should endeavour to engage the stakeholders in an emotional debate to understand their emotional concerns. This proactiveness may foster collaboration that allows the project developers and the community to influence each other with their worldviews to co-develop solutions that ensure that the project does not compromise their safety and those they care for. This reaction towards the industrial actors and the government is also in line with what Ashworth et al. (2011) observed in the Dutch case in the toolkit (Ashworth et al., 2011). For example, in the Dutch case, lack of trust in the local government contributed to the disapproval of the storage in Barendrech. According to Ashworth and colleagues, the people felt that the decision of the government and the project developers to store the CO2 in Barendrecht was not because it is a safe place. Instead, they felt that it was the cheapest place to store the CO2 which amount to lack of integrity-based trust in line with earlier findings by Terwel et al (2009).

4 Discussion and Conclusions

In this work, we revisited the work of Ashworth and colleagues' Communication and Engagement toolkit for CCS projects. The toolkit is designed for implementers of CCS project for understanding the social context where the CCS project will take place to enhance deployment. Upon appraisal of the context, we observed that the SWOT tool recommended for the practitioners in making predictions to guide strategic decisions to enhance deployment is weak, for the purpose recommended for. To overcome this limitation, we have proposed an alternative method based on artificial intelligence. As demonstrated in the results, the proposed approach has the capability to learn from sample data and develop capability to predict unseen behaviors to guide decision-making. One may ask, why should we care for this method in the field and in relation to the recommended SWOT in the toolkit for prediction to guide strategic decisions. The implication is discussed.

4.1 Implications of the AI tool on the toolkit for practice and theory

To appreciate the value adding of the AI tool on the toolkit, let's recap some statements that were briefly highlighted in the introduction sections, expand upon it, and use it as a point of departure in the discussion. Why did Ashworth and colleagues recommend SWOT as a strategic tool? In the toolkit, it is stated that the SWOT "could be performed after the qualitative and quantitative data has been collected, giving the developers a better ability to make recommendations and predictions based on un-biased, factual evidence" (Ashworth et al., 2011, p.34). This statement leads to reflection of the following question; what it means to learn from data to be able to predict, and what the role of SWOT is as a strategic tool in achieving this goal. As highlighted in the introduction, the prior work of Breiman (2001) and Shmueli (2010) have an answer. According to their findings, there are many ways that science can learn from data to study our social and natural world. It can loosely be grouped into two main school of thoughts: (a) explanatory modeling, and (b) predictive modeling. Regardless of the assumptions and limitations of each school of thought, learning from data is the common denominator for both approaches. What differentiates the two schools of thought are their primary goals and the tools the scientists use to exploit the data and achieve their goals. The authors findings explained that explanatory modeling is the use of statistical models for testing causal explanations. Some of the tools used in explanatory modeling includes linear regression, logistic regression etc. Predictive modeling on the other hand, is the process of applying a statistical model or data-mining algorithm to data for the purpose of predicting new or future observations. The predictions include point or interval predictions, prediction regions, predictive distributions, or rankings of new observations. Therefore, predictive modelling is any method that produces predictions, regardless of its underlying approach" (Shmueli, 2010, p.291). It means that prediction is not synonymous with causal explanation. In prediction, it is about what will happen given new observation or what is the best among alternatives (ranking). Some of the tools used in predictive modeling includes neural networks. This explanation leads to these questions: (a) What is the role of SWOT in the science of prediction? And (b) What is its capability of making accurate predictions given new observations.

A vast amount of studies is in consensus that SWOT as a tool is a good strategic tool for developing qualitative predictions. For example, the strength of a conventional SWOT is that it can help the practitioners to identify the strengths, weaknesses, opportunities, and threats to their proposed project. This can help them develop both qualitative and rough evaluations of their competitiveness. This information can then be used as a foundation for the development of CCS communication and engagement strategies, as suggested in the toolkit. Despite this ability, a considerable number of studies point to limitations in the SWOT tool that could limit the practitioners' efforts to quantify the future to gain better insight into the future.

First, conventional SWOT does not consider any priorities for the various factors. Only qualitative examinations of the environmental factors are considered. Secondly, it does not give weight to the sub-criteria that could enable the project developers to prioritize the data collected. Furthermore, the analysis is static and rarely results in the development of clear alternative strategies. It does not consider the priorities for various strategies so that the SWOT results in a clear understanding of the effectiveness of the strategies proposed by the project experts in relation to the sub-criteria ((Hill & Westbrook, 1997; Ekmekçioğlu et al., 2011; Haile & Krupka, 2016). Finally, SWOT analysis has been developed based on stable environment that means if the environment of an organization were steady, invariable, and predictable, the classic SWOT analysis could be performed for the organization. In today's world, environment of organizations is stormy, fast changing, unpredictable, and with uncertainties. It is similar to the social context of CCS projects. CCS is a complex socio-technical system with multiple social participants. These social participants have their own value-set and power to influence the system. For example, in their technical report in 2015 titled "Carbon Capture SCAM (CCS)," Greenpeace, an environmental NGO, described CCS as an environmental scam that industries are using to promote the continuous use of fossil fuels instead of taking more radical action. Despite this negative reaction to CCS, other NGOs, such as the Global CCS Institute, have described CCS as a good technology. The Global CCS Institute stated that, without it, it would be impossible to achieve the 1.5- and 2-degrees ambitious target in the Paris agreement. The different value-sets of the actors and their power-in-transition in CCS social-technical systems are among the factors that contribute to the uncertainty around the reception by different stakeholders of individual CCS projects around the world (Avelino, 2017). This uncertainty is what made Taghavifard et al. (2018) state, "When [the] future is predictable, common approaches for strategic planning such as [SWOT analysis] are applicable; nonetheless, vague circumstances require different methods. Accordingly, a new approach that is compatible with uncertainty and unstable conditions is necessary" (p.1). The study of Shinno et al. (2006) and Chermack and Kasshanna (2007) support this finding and add that for conventional SWOT to move to the level of strategic thinking to meet the requirement of prediction as defined by Shmueli (2010), it needs to be augmented with other regression techniques.

Overcoming the above stated limitations is where the AI tool we have proposed based on the toolkit is best suited for the predictive task expected by Ashworth and colleagues in the toolkit. As explained in the theoretical framework and demonstrated in the experimental results, the proposed AI tool leverage the practitioners of the time consuming probabilistic task on the problem under observation. This allows them to focus on the cognitive tasks on the problem which are unique to humans due to our wisdom. This human and machine cooperation facilitates speed of decision making. Its because a vast amount of studies has shown that algorithms are fast at the probabilistic task in relation to humans' capability even though humans guides its development. This is why we usually read or hear in the media that algorithms have, for example outperformed human experts in predictive tasks including medical diagnosis (see e.g. Steele et al., 2018). It's not because the AI algorithms, for example, are smarter than the human doctors or domain experts since algorithms are no where near human intelligence. It's because of their ability to discover complex patterns in a data beyond causal interaction to predict future events. This complexity in the data may escape human observations, for example, when there is nonlinearity in the data at hand.

For example, in standard practice in the social science literature on CCS, the low predictive power of the SWOT in the toolkit could be enhanced by using linear regression-based modelling or causal modelling. In this modelling strategy, domain experts lead the construction of the model using expert-driven theoretical hypothesis based on underlying theory (see e.g Midden &Huijts, 2009; Terwel et al, 2009; Yang et al, 2016; Huijts et al., 2019). This expert-driven approach has a merit and has contributed novel knowledge in the field of CCS. However, the findings of both (Bremain, 2001; Shmueli, 2010 and Yarkoni & Westfall, 2017) agree with our assertion that the predictive power of the expert-driven approach is low. It's because they are primarily oriented towards causal explanation and not prediction. It is important for us to emphasize here that; eventhough regression models such as linear regression is an explanatory technique, but could produce accurate predictions when the SWOT is fused with it. It is especially the case when we have few parameters with few nonlinear linear dependencies among the parameters. However, Bremain (2001) and; Shmueli (2010) observed that it may lead to inaccurate prediction when the parameters become large with many nonlinear dependencies among them. But that is the nature of human related data, including those qualitative and quantitative data collected to observe the social context of a CCS project. Human related data is a high dimensional data. High dimensional data contain many attributes with many non-linear dependencies. Due to this characteristic, as data becomes complex, human experts' ability to look at the high dimensional data on the problem, discern patterns and their non-linear relationship to construct a causal model and fit to a data to predict a behavior, can be challenging. In this context, if we are to solely rely on the human experts' assumption of the relationship among the parameters, it may be challenging to be accurate in the observation due to the complexity.

As demonstrated in the experimental result in Table 5, the proposed AI tool provided the practitioners with a mathematical framework to learn from the social data about the CCS project to make guesses of the future. As indicated in the architecture of the AI tool, this social data is not limited to SWOT factors. It depends on the problem under observations. For example, in the experiment, we demonstrated by how we can learn from the social data about the CCS project to predict how the citizens will emotionally react to a strategic option in the modified SWOT matrix in the project developers' external environment. In this analysis, it could be observed in the experiment that the learning resulted in a development of a model with high predictive power. The algorithm was able to use this capability to predict the future behaviors on the CO_2 storage on the 84 out-of-sample respondents without necessarily relying on the people to tell the project developers how they feel. A study by Buah et al (2020) support this approach and add that such predictive capability limits social desirability bias in the communications and engagement process especially in the face-to-face consultation approach. Social desirability bias occurs in the face to face engagement workshop. It is when some of the citizens and stakeholders who influence the project, are unwilling to disclose their true feelings about the project if they perceive the answers to be socially undesirable. Assuming the true feelings is negative, this cognitive bias may deceive the project developers to think that all is fine for their stakeholders, but in reality it is not. But only to leverage their true feelings over time to disapprove the projects if they could do so as part of collective action anonymously, if the agenda for disapproval, aligns with their true feelings,

Gough et al (2018) supports this assertion and add that it may happen because the fact that a CCS project has initially been approved do not suggest that it has achieved its social license. Overtime the social license could be withdrawn because it is neither legally binding nor a one-time approval of the project. This suggest that the algorithm's capability to make accurate guesses of the true feelings, could complement that of the feelings observed in the face-to-face workshop to gain insights into what might be close to the reality to guide decision-making.

In our subjective opinion, this approach to understanding the social context of the project may help the practitioners to be proactive. In this way, they could devise appropriate interventions to properly engage the stakeholders, instead of waiting for something to happen or the people to always tell them how they feel for them to be reactive. Whilst being reactive may not be a bad thing, in an urgent situation, the project developers may be tempted to take a top-down approach to impose decisions. The decisions may not be in the best interest of the people, and leads to a new turn of events. It may be the case, especially when, for example, the withdrawal of the social license is unexpected by the project managers.

4.2 Concluding remarks, limitations and future studies

In conclusion, one of the novelty of the proposed AI tool for CCS is that it is not a static model unlike the SWOT tool recommended in the tookit. The proposed system is a learnable and dynamic system. It can take any number of input information without limiting to for example, strengths, weakness, opportunity and threats. The structure of the input data can change depending on the problem under observation and essential predictors that could shed light on the problem.

Another unique characteristic of the AI tool lies in its computational foresight thinking. The data used to train the algorithm do not become obsolete over time. It is unlike, for example, when constructing a causal model, and the context change, but the problem remains the same. If the context changes and the problem remain the same, the model just needs to be retrained with a sample data of the new context and it will automatically adapt its initial weights to the new situation with little or no human influence.

In this optimization and adaptation, it discovers new complex and hidden patterns that was may be initially overlooked by the algorithm to develop new hypotheses that could predict the future, given new observation. The theoretical value of this capability is that; the model could become a test-bed for theorists in the field observing the problem. It can augment their knowledge on the problem by enabling them to simulate and experiment different scenarios to develop and test new theories with practical implication.

Also, as it was observed in the experiment, the proposed AI model is not limited to the big data requirement unlike the conventional deep learning algorithm. It is flexible with data. The system has its own internal data augmentation technique to mathematically hack into small data of a few hundreds. This flexibility helps to optimize the decision-making process, given that, it is expensive and time consuming to collect big human related on CCS project and analyze it in a timely manner. In future work, we recommend the tool for our colleagues to apply it in a different context to solve many challenging problems in the CCS value chain because of its adaptable nature. For example, improving the efficiency of the carbon dioxide (CO_2) capture process requires a good understanding of the intricate relationships among parameters involved in the process. This can be challenging or time consuming for experts. The proposed system can support the project developers in this task. It can help them to harness the few available process data points to design an intelligent algorithm. This algorithm can then be applied to the problem to examine the intricate relationships to predict the CO_2 production rate to improve the efficiency of the CO_2 Capture process and we recommend it for future studies.

All in all, the proposed AI tool for CCS is without its own limitations. Even though when the proposed method is applied, the outcome is an explainable model. It means that model is not only accurate but also interpretable. It is important for us to however emphasize that the model interpretability capability is causal inference, and not causal explanation. This suggest that the proposed method is poor at causal explanation in relation to the traditional approaches underlined in the discussion. In this context, in a problem where our colleagues are interested in causal explanation, we will recommend the use of the traditional models, since they are better at it than the method being proposed.

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Appendix 1: Predictors associated with the five constructs used in the experiment

Table 1 Predictors used in the simulation experiment to predict emotional response to the CO_2 storage nearby

P	Predictors	P	Predictors/expected outcome
P1	Competence-based trust (CBT): Government of my country	P14	Risk perception: Bad effects on trees and plants by sudden leakage of CO_2
P2	CBT: Industry (e.g. utility companies, oil and gas companies)	P15	Risk perception: Bad effects on human health from leaked CO_2
P3	CBT: Environmental non-governmental organizations (NGOs)	P16	Risk perception: Pipeline being destroyed by earthquake
P4	CBT: Environmental Protection Agency (EPA) of my country	P17	Risk perception: Bad effects on soil from leaked CO_2
P5	CBT: Scientists and engineers in my country	P18	Risk perception: Acidification of sea water by leaked CO_2
P6	Integrity-based trust (IBT): Government of my country	P19	Risk perception: Pipeline being destroyed by corrosion
P7	IBT: Industry (e.g. utility companies, oil and gas companies)	P20	Risk perception: The reservoir containing the CO_2 being destroyed by earthquake
P8	IBT: Environmental non-governmental organizations (NGOs)	P21	Benefit perception: Myself
P9	IBT: Environmental Protection Agency (EPA) of my country	P22	Benefit perception: My family
P10	IBT: Scientists and engineers in my country	P23	Benefit perception: My future children yet unborn
P11	Trust in actors as a team	P24	Benefit perception: The environment

P12	Overall risk perception towards CCS	P25	Reaction to proximity of the CO_2 storage
P13	Risk perception: Sudden release of large amount of stored CO_2	P26	Affective feelings toward the CO_2 storage nearby (expected output)

For more details about the questionnaire used to implement and measure the predictors in Table 1 see the work of Huijts et al. (2007); Midden and Huijts (2009); Xuan and Wang (2012) and Terwel et al. (2009).

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