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The Path to Carbon Capture Technology Adoption—A System Dynamics Approach

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Abstract

A system dynamics approach is described to explore the path of Carbon Capture diffusion. The proposed model, in principle, follows the Bass diffusion of innovation theory and includes all major influencing factors. The primary contribution of this paper is the modification of Bass's model to reflect parameters affecting the adoption of Carbon capture and storage technology. Consequently, it differs from other extensions to Bass's model. The underpinning of this work is the system dynamics (SD) approach, which can open a pathway for further research into CCS acceptance. The proposed model's behaviour is illustrated for various transition pathways of the technology, for different regimes. By modifying the proposed model, the paper also allows consideration of various capturing technologies on their merit. The proposed framework enables the examination of the impact of intervention policies on the adoption of CCS by individual investors. The purpose is to identify the parameters of these policies to support the under-resourced CCS technology and reduce the need for government participation. It is worth noting that the SD is primarily a descriptive method used for scenario analysis to illustrate what the future would look like.

Keywords: carbon capture chain (CCS); technology diffusion; system dynamics; system thinking; innovation acceptance; innovation adoption

1. Introduction

Technology diffusion has been examined through various interconnected perspectives, including public acceptance, product lifespan, and organisational effectiveness. This suggests that every facet of technology plays a critical role in its overall impact. Diffusion refers to the transmission of innovation over time through specific communication channels among members of a social system. The phenomenon of technology diffusion has been examined through a diversity of interconnected viewpoints, including [1]:

1. Communication feature: It assumes that for potential adopters, the novelty of innovation is uncertain, and aside from a few early adopters, most tend to avoid risks.
2. Economic feature: It looks at how suppliers cut innovation costs and make it more valuable for users.
3. Market and regional features: This relates to regional geography and emphasises that limited product availability can restrict market penetration and innovation.
4. Affordability feature: While people in rich countries often have easier access to resources, developing countries face bigger issues with income and wealth inequality.

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5. Investment culture feature: In some societies, all resources are used to meet daily needs, leaving no surplus for future growth.

Considering these perspectives helps us better understand the diffusion of technology and its outcomes. This paper presents individuals with surplus assets to invest and their views on CCS technology.

Technology diffusion is the process of spread and adoption by users, sectors, and regions that can help policymakers decide on effective strategies to foster innovation. The objective of the diffusion model is to identify the factors that influence adoption, such as performance, profitability, suitability, learning effects, and social norms. Researchers have employed a range of tools to understand the reasons behind the adoption of innovative technologies.

In this article, technology acceptance and adoption are not the same. In other words, they are not impossible. Acceptance is a mental or emotional state of coming to terms with something, while adoption is an action of taking on or using something as one's own. Acceptance is the first step towards adoption; you must first accept certain factors (such as a new technology or idea) before you can choose to adopt them.

Technology diffusion is a dynamic and time-bound process that involves the exchange of information, knowledge, and innovations. It shows the steady, gradual spread of new ideas across vast and diverse societies [2]. Efficiency and techno-economic feasibility govern the diffusion of technology [3]. Models of technology diffusion describe the drivers, patterns, barriers, and pathways to adoption. Depending on the context and the level of effort, these models employ various assumptions and data. A fundamental assumption in all innovation adoption is that adoption growth follows an S-shaped curve: it starts gradually, accelerates, and levels off. Epidemic models inspire technology diffusion models, as they are driven by social interactions and learning (or contagion) among potential adopters. The spread of rumours, infectious diseases (like COVID-19), knowledge, and so forth follows the same path as the adoption of innovation.

Such models can aid in evaluating the path to technology diffusion, including return on investment, health concerns, and environmental impact. The efficacy, cogency, and cost-effectiveness of various strategies and intervention policies to promote technology can also be assessed.

Data quality and availability are significant issues, as reliable, comprehensive data are often unavailable. Assumptions made to simplify the model can impact the validity and robustness of the results, potentially underestimating the complexity of technology diffusion or rendering the model irrelevant for specific policies or objectives. Nevertheless, System dynamics models are continually evolving and improving.

The Global CCS Institute currently monitors 50 operational projects and 628 projects in various stages of development worldwide. However, to make a significant impact on carbon emissions, approximately 75–100 facilities need to be built per year [4,5]. The installation of several CCS plants over the past decade is a significant step towards adoption, but until a cost is associated with pollution, no technology will take off. However, most of these plants have considerable government backing. Potential investors are hesitant to adopt such technology due to uncertain returns on their investment and regulatory uncertainties. To mitigate CO2-driven environmental degradation, some national governments introduced regulations for the power generation industry. Policy instruments are mostly various forms of economic incentives or standards that impact electricity prices [6].

Scholars of diffusion theory have developed several analytical models to explain and predict the dynamics of technology adoption among potential users. The diffusion of CCS technology is a closed system in which output influences input; namely, the acceptance of CCS is influenced by its past performance. Considering these, the System Dynamics (SD) approach is an appropriate tool for studying such closed systems [7]. The starting point in building a system dynamics model is identifying the system's variables, their relationships, and the strengths that influence the system's behaviour through feedback. The positive or negative relationships are referred to as causal or feedback loops [8]. The Dynamic interaction between two or more system parameters can cause distinct behaviours, such as lockout or bridging, phasing out, and the diffusion of one or more alternatives [8].

Additional complexity arises from the international nature of CO2 emissions, as each nation has its own policy for reducing them. CO_2 emissions affect countries differently, leading to diverse preferences, priorities, and environmental policies. These influencing factors contribute to uncertainty in determining whether and how a national government will adopt CCS. Since nation-states have different priorities, understanding them is significant.

Bass's diffusion model of innovations has been used to study innovative technologies [8,9]. Bass' model utilizes a few variables, and sales data are used for parameter estimation. However, such data for CCS (or even for an analogous technology) are nonexistent. Some national governments do not consider climate change an urgent issue or believe it is someone else's problem. Bass's model has been extended since his original work, and this research is another contribution to this body of work. Diffusion theory is widely applied across various domains [10,11]. The current model-based approach seeks to gain insight into ways of maximising investor acceptance under resource constraints. The term "investors" in CCS refers to those who are willing to invest in CCS as part of their investment portfolio.

The diffusion of innovations over time is a highly dynamic and complex problem. Traditional models of innovation overlook several key influencing factors; as a result, they fail to adequately represent all relevant issues. Milling and Maier provided an overview of extensions to the rational models and their performance [12]. They also note that the use of the system dynamics methodology allows the development of more complex models to investigate the process of innovation diffusion. However, Milling and Mair [12] extended Bass's model to incorporate competition and to map the process of substitution among successive product generations, which are not issues concerning CCS.

System dynamics (SD) is a helpful tool for modelling the diffusion of Carbon Capture and Storage (CCS) technology because it can simulate the complex, non-linear interrelationships, feedback loops, and time delays that influence technology adoption.

- SD models integrate all the components of the CCS value chain (capture, transport, and storage) as an integrated system, allowing for a comprehensive understanding of the entire process.
- It is suited to identifying feedback loops, such as how a promotion leads to "learning effects", which in turn accelerate further adoption.
- It can be used to examine the influence of various policies, such as tax credits, carbon prices, subsidies, or emission performance standards, on the adoption rate of technology.
- Decision-makers can examine various scenarios to gain insight into long-term outcomes of different decisions, thus identifying possible risks and how to mitigate them.
- SD can include many influencing factors, such as the behaviour of socio-technical systems, as well as the public perception, regulatory regimes, and business concerns.

System dynamics was used to understand long-term interactions between technical, economic, societal, and political factors that influence the transition from fossil fuels to clean energy. This approach uses feedback loops, time delays, and other tools to create simulations that test different policies, assess the impacts of strategies such as renewable energy integration and energy efficiency, and understand how systems evolve. It facilitates the comparison of different transition pathways and identifies key leverage points to accelerate the transition to a sustainable energy system. A few of such contributions are shown in Table 1. See also references therein.

Table 1. Some recent applications of the System Dynamics method to the transition from fossil fuels to clean energy.

Reference	Contribution
[13]	The paper explains how adding ideas from social and technical studies can make quantitative energy transition models more realistic. They also explore how system dynamics can be used to study energy transitions and highlight how it differs from traditional econometric and linear programming models.
[14]	The study developed a system dynamics model and tested major policy scenarios to explore how Singapore's electricity sector could achieve better outcomes by 2100.
[15]	The research examines whether integrating CCS technology into a traditional power company's long-term strategy is reasonable. Using a system dynamics model, the paper assesses how CCS could affect environmental and economic outcomes in carbon-trading and renewable-energy contexts.
[16]	The study establishes a system dynamics model of the energy transition that captures interactions among political, social, energy, emission, and improvement elements using feedback loops. It concludes that achieving the UK's net-zero goal may face greater social and political challenges than those suggested by traditional techno-economic energy models.
[17]	The paper investigates how expanding the share of renewable energy affects the overall energy mix for both primary energy supply and electricity generation. A system dynamics model is used to examine its quantitative influence on key energy security indicators.
[18]	The authors highlight that most sustainability transition research depends on qualitative socio-technical transition (STT) contexts, yet modelling can serve as a helpful supplement. The paper reviews five system dynamics (SD) energy models to assess how well they capture major descriptions of STT.
[19]	The study examines how safety culture, as part of an organisation's overall culture, affects safety performance in a post-combustion carbon capture plant. A system dynamics model was developed using key safety culture variables to explore their impact on overall safety results.
[20]	The research analysed the safety approach for hydrogen transport infrastructure. Using a system dynamics model, it considered technical aspects such as material degradation, pressure changes, and the effectiveness of monitoring systems, all of which impact hydrogen transportation safety.
[21]	The research examines the role of safety culture in shaping the safety performance of blue hydrogen projects. Key elements affecting safety culture are identified, and a system dynamics model is created to assess their influence on overall facility safety. The findings emphasise that prioritising safety culture is crucial to an organisation's long-term sustainability.

Specific issues associated with the CCS adoption process make SD a suitable tool for studying this process. SD's focus is on relationships between the system's variables, in which causal relationships are established and followed over time as attitudes change and the public becomes aware of the impact of CO_2. SD modelling strips away complexity by focusing on key variables, thereby making the system's behaviour comprehensible and within reach. Thus, it enables testing of probable consequences of various strategies [8]. As such, it is a descriptive, rather than a predictive, tool [8]. The objective of SD is to gain insight into the influence of various variables, understand change patterns, and identify gaps in understanding.

The objective of this paper is to lay a foundation for extending Bass's diffusion theory to simulate the adoption of CCS using systems thinking and the SD method [22]. The process of implementing CCS technology consists of a sequence of steps designed to reduce CO_2 emissions from industrial sources. The focus is on capturing the dynamics of CCS technology adoption and identifying gaps that require further research.

Technology acceptance follows technology adoption in an innovation decision process. Rogers and Ward have identified "five phases" [10,23]:

- Knowledge base: learning about the use and function of innovation.
- Perception: favourable or unfavourable.
- Decision: An investor who chooses to adopt or reject the innovation.
- Pilots: making use of innovation.
- Endorsement: The final acceptance or rejection of the innovation.

The innovation decision-making process begins with modelling the technology adoption. The next phase is the acceptance of technology, followed by a decision on whether to invest (adopt) or reject it. The actual use of technology is referred to as technology acceptance, implying that adopting a technology does not necessarily mean ultimate acceptance.

The usability of a system is defined as the 'system's suitability and usefulness.' This, in turn, is "influenced by the end-user's behaviour as well as the characteristics of the environments in which it will operate [24]." According to Jordan et al., the usability measures must be [24]:

- The ability to deliver sound, actionable results.
- Efficient use of resources.
- Users' satisfaction.

This study aims to understand the factors influencing the sustainable adoption of CCS and the behaviour of investors as they navigate the complexity of CCS implementation. This paper develops an SD model of CCS implementation, which is subsequently verified, validated, and finally tested. The objective is to explore ways and means of diffusing carbon capture technology for long-term emission control based on insights from the SD into the nature of innovation diffusion. Without a better understanding, stricter emission-reduction targets may be necessary, which could prove impossible for nations to meet and therefore have little chance of success. It is believed to keep the option of removing carbon alongside the use of wind and solar energy. However, policies needed to make advanced technologies accessible and affordable require increased research and development, demonstration of their operation, and support for new installations, standardisation, and infrastructure. The pursuit of economically viable methods to achieve near-term emissions targets overlooks the long-term solution, such as carbon capture and storage.

Finally, this paper focuses on the acceptance of CCS by small investors rather than its adoption by governments. There are several limitations in developing this mode. The main limitation is a lack of reliable data, both primary and secondary.

2. Materials and Methods

2.1. The Bass's Diffusion Model and Its System Dynamic Representation

The concept of diffusion is frequently invoked in social contexts (e.g., the spread of rumours), epidemiology (the spread of contagion), and marketing (the adoption of innovative technology), among others [25]. A product may experience rapid sales through word of mouth (W-o-M), but eventually the growth curve flattens as the pool of potential adopters gradually diminishes. The Bass model attempts to capture this dynamic behaviour.

The model assumes that the new adoptions (purchases) are related to the number of prior users (buyers) [9]. However, it provides a reasonable fit for the sales peak, and it aligns with historical data. The ability to estimate the sales peak and its timing could assist with capacity planning and distribution strategies. Figure 1 "shows an SD representation of the Bass model, which shows that novel technologies require the passage of time to be adopted by all potential users and the diffusion process to take hold [26]." "This form of the model is like the basic epidemiological model [27,28]." A sizable number of research papers utilise the Bass diffusion model [29–35].

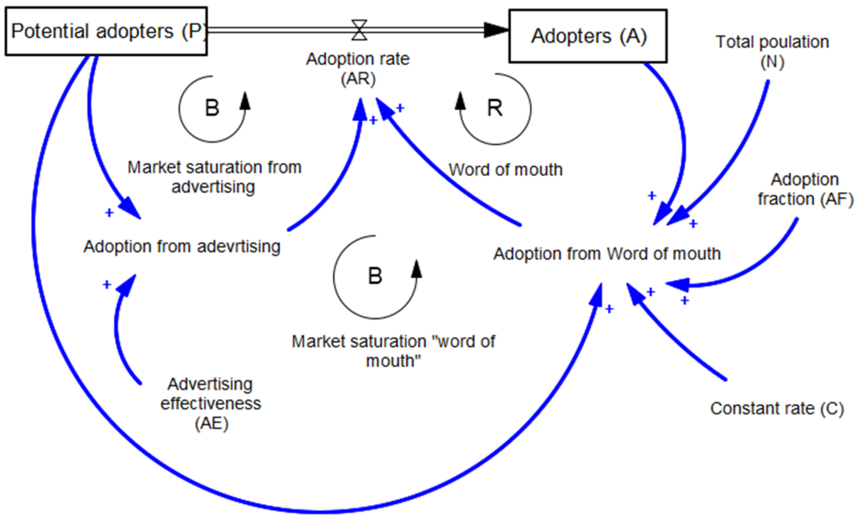


Figure 1. An SD representation of the Bass diffusion model (based on Sterman, 2000) [8].

The SD model of Bass's diffusion theory consists of (Figure 1):

1. Stocks—indicate the system's state and provide data for decision-making.
2. Flows—influence the level of stock.
3. Auxiliary variables—link each other and hence could influence each other, allowing for the identification of the cause-and-effect direction in the model.

The model in Figure 1 shows two stocks: Potential Adopters (P) and Adopters (A) of the Technology. The increase in the Potential adopter (P) increases the Adoption rate (AR), which is also influenced by other auxiliary variables, namely, Adoption from advertising and adoption from Word-of-mouth (W-o-M). Potential adopters and advertising effectiveness also impact adoption through advertising. The buying due to the W-O-M consists of the purchaser variable and the Total population (N), the contact rate, and the purchase fraction, which are constants. Figure 1 shows one reinforcing feedback loop (R) and two balancing loops (B1 and B2).

Many papers describe several reasons for adopting a novel technology using a variety of tools. In the 1960s, Bass developed a mathematical model known as Bass theory. However, Bass used a few variables in constructing his model, and various researchers have since extended it. "Sale data is required for estimating Bass's model parameters [36]." However, the required data on CCS technology (or an analogous technology) are not available, as some national governments do not collect or publish data on the urgency of climate change.

In the absence of real data, simulation is a good alternative for studying complex systems, such as the acceptance of CCS over time. The adoption can be investigated by the system dynamics (SD) version of the Bass model. The system dynamics version of the Bass model can be used to study adoption. SD's focus is on relationships between the system's variables, in which causal relationships are examined and, over time, may lead to changes in behaviour. SD modelling is a way to strip away complexity by focusing on the important variables, thereby making the behaviour more comprehensible. This, in turn, enables testing the probable consequences of various strategies. SD is not a predictive tool, but it is a descriptive one. The objective is to gain insight into the change pattern and to identify gaps in understanding.

System dynamics (SD) can be used to model the diffusion of Carbon Capture and Storage (CCS) technology by accounting for feedback loops that influence its adoption. These models use a range of variables, including policy incentives, economic factors such as costs and learning effects, technical feasibility, public acceptance, and stakeholder interactions, to analyse the long-term, nonlinear impacts of large-scale CCS implementation. SD models can help identify key drivers, such as the effectiveness of subsidies or the effects of learning-by-doing on costs, and explore different scenarios to inform strategic decision-making for policymakers and businesses aiming to achieve decarbonisation goals.

This paper extends the existing SD version of the Bass model for simulating the CCS path to adoption. The focus of this paper is to capture the dynamics of CCS acceptance and identify gaps in existing knowledge.

There are four components in Bass's diffusion model:

1. An innovative idea,
2. Letting interested people know via accessible communication channels,
3. An elapsed time giving people time to become aware, and
4. A social system that permits the diffusion to take place.

The characteristic of an innovation is its novelty to individuals (investors in this case), rather than its novelty to the world. Information regarding Innovation is communicated through specific channels by individuals who are aware of it to those who are unaware. These groups of scientists advocate for the adoption of CCS through publications, seminars, and interviews. A specific elapsed time is required to convey knowledge effectively through these channels. All these individuals belong to a social network with defined boundaries. The perceived usefulness of technology influences the time that it takes to adopt novel technology, suitable means of communication (e.g., advocacy groups' activities, popular media reporting, communal interactions, and so on), the internal rules governing the social network, the stretch and strength of promotional works, as well as the nature of innovative technology.

In a CCS chain, multiple interested parties must collaborate to facilitate technology adoption. The multinational nature of CO_2 pollution makes it difficult to force polluters and free riders to share the burden. Countries with varying levels of CO_2 emissions, which affect nations differently, lead to numerous environmental policies. These influencing factors do not reduce uncertainty about whether a nation would adopt CCS. Since nation-states have the final vote, understanding their concerns and priorities must be the first step.

Many CCS projects undertaken over the past decade are expected to have a beneficial effect on adoption. However, all these plants have large government subsidies. Private investors are not yet ready to adopt CCS technology due to the uncertain return on investment.

The system dynamics methods are a valuable tool for studying the diffusion of a carbon capture facility as a complex system. The system dynamics approach enables feedback among variables and time delays, characteristics that are also present in several economic issues and management systems, as well as in CCS systems.

SD methods can combine the effects of system behaviour (physical, technical, and combined), human, psychological, and financial factors in the study of technology management and innovation. Maier has applied SD to study problems associated with technical change and the diffusion of innovation. Various factors, including price, advertising, and product capabilities, influence the diffusion of innovation [37].

"The adoption of novel technologies often obeys an S-shaped or logistic growth curve. The observed S-shaped behaviour is believed to be driven by a reinforcing feedback loop that causes initial exponential growth, followed by a balancing feedback loop that limits that growth. Reinforcing and balancing feedback loops are the result of uncertainty associated with innovation {8]." A more complex SD model of innovation diffusion should provide insights into the effects of advertising, mass media reports, lobbying efforts, and other factors.

2.2. CCS Diffusion Model

A technology-led approach to mitigating CO_2 emissions is discussed by Galiana, Green, and Neij, among others [38,39].

The primary factors influencing CCS technology acceptance are:

- The CCS technology readiness must be at TRL 7, or at least TRL6 [40–42]. Technology has been employed somewhere in the world (pilot or commercial scale), or the concept has been proven by prototyping.
- Promotion by advocacy groups so that investors become aware of it.
- Enablers, such as regulations and cross-border treaties for conveying the captured CO_2 to a suitable storage facility, which require cross-border cooperation, and the time horizon over which this could happen.
- The public acceptance, i.e., a social system that makes the acceptance of technology possible.
- Profitability for investors or direct investment by the government as a societal service.

CCS technology is a novelty to an individual (investors for this paper), but it is not novel to the world at large. Different nations have varying levels of technological awareness. Ways to exchange information and impart knowledge to individuals or organisations are referred to as communication channels here [43]. The diffusion of new ideas takes time, as individuals need to become comfortable with a new concept.

The time that an investor requires to adopt a new technology depends on the time needed for perception of profitability and attributes through communication channels (e.g., through social interactions, popular media, and seminars), the regulatory regime, the intensity of promotion efforts by the advocacy groups (researchers and learned societies), national and international laws and treaties, and the extent of willingness to commit capital.

Modelling of technological innovation has attracted the attention of several researchers [44–47]. We have conducted a literature survey to identify the barriers to CCS technology adoption identified by researchers. The purpose was to determine the key variables and their causal relationships [48].

Four stocks and four flows are shown in Figure 2. Stocks represent the total number of all possible investors at various stages of adoption. Flows refer to the rate at which investors move from one stage to another. One of the following four primary variables controls flows:

1. Innovation's perceived attributes
2. Means of communication
3. Promotion by advocacy groups. and
4. The social system.

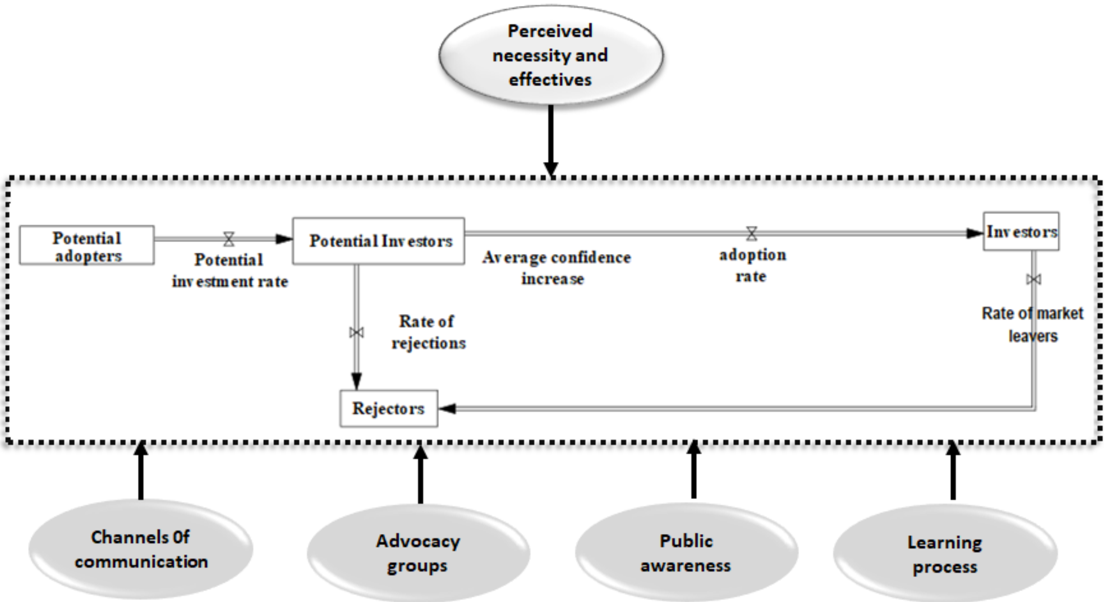


Figure 2. These figures present the model concept and illustrate the boundaries of the framework used to analyse CCS adoption. Four stocks represent the total number of possible investors at various adoption stages. Four flows represent the rate at which investors move from one stage to another.

The framework in Figure 2 is viewed from the investor's perspective, meaning that decisions are neither made individually nor collectively. There are more stocks and flows in the representation than in the basic Bass model. Additionally, it assumes that investors become adopters, as well as active rejecters, after they have had the opportunity to be exposed to technology.

Figure 3 shows that two additional stocks are used to differentiate between investors who are merely tempted to invest and those who have made up their minds to adopt or reject the technology, following specific considerations. The stock of "Investing population" represents the investors who are actively considering it. The "Potential investors" stock represents investors who are likely to adopt the product or service after becoming aware of it.

"Two feedback loops of B1 and B2 are the market adoption or adoption through advocacy groups (known also as external influencing factors), and word-of-mouth (known also as internal influencing factors) [8,49]". These are two separate information channels. "The external influence starts the process of adoption by early adopters, who then initiate W-O-M in the population (individual investors for CCS) among potential adopters [50,51]. A fundamental assumption of Bass's model is a perfect mix of a collection of individuals whose behaviour is similar and can be aggregated. As a result, the variables' numerical values are the group average. A primary assumption of the Bass theory is that the cumulative growth of adopters over time resembles an S-shaped curve.

Multiple verification and validation tests were undertaken to ensure the right question was answered and the answer was also correct [52,53]. These validations included pushing the model to the extreme and obtaining Bass's results. The model's validity and applicability were assessed by whether the results were consistent with knowledge of the CCS and analogous systems. Information from the literature is used to verify consistency checks, ensuring that variables and the causal relationships identified in the literature are accurately presented in the model.

The model produces the expected S-shaped characteristics while approaching approximately 20% of the average of the "Average investors' familiarity" variable for the year 2020, as shown in Figure 4, which shows Bass's classical shape of innovation acceptance.

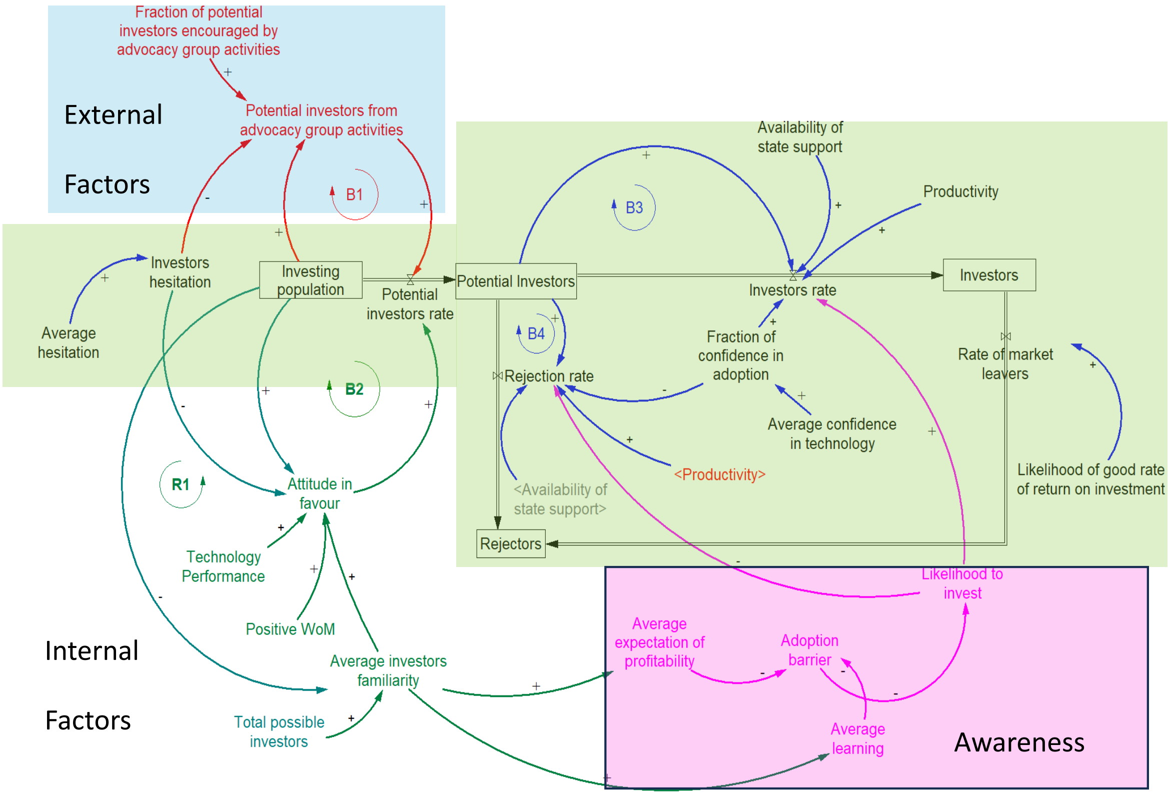


Figure 3. This is the software output from the proposed model, a modification of the Bass diffusion SD model. It shows the four subsystems in the model, each dedicated to a group of variables.

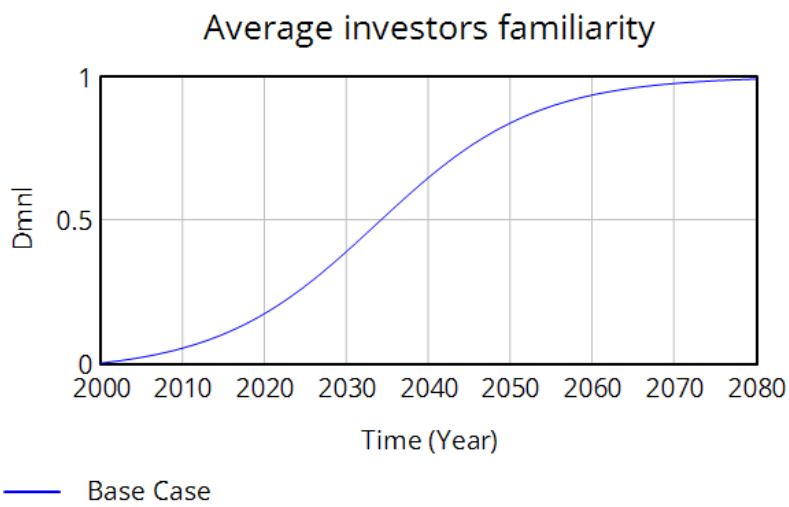


Figure 4. Average investors' familiarity from 2000 to 2080. This figure indicates the classic shape of the innovation acceptance curve. Changing the variable's value (for example, the timing of the government subsidy) creates a bump in the curve, as expected.

The model is composed of the following four subsystems:

1. The decision-making subsystem, which is the backbone of the whole system.
2. A subsystem that represents the external influencing factors, which are researchers, learned societies (advocacy groups), learned journals, and, to some extent, the news media.
3. A subsystem that represents the internal influencing factors (primarily W-o-M).
4. Awareness subsystem, which represents the passage of time that causes investors to know more about a novel idea and become comfortable with it as the technology is improved.

The decision-making subsystem maps the path by which "Potential investors" become "Investors," possibly decide to invest in the technology as a first step, and are willing to participate in financing a CCS project.

The external influence subsystem—also referred to as external factors in the literature—encompasses promotional activities from educational campaigns, supplemented by media (mass and academic) promotional efforts. These communication channels can transform "potential investors" into actual investors, who then spread beliefs by Word of Mouth about the technology, and hence activate the internal factors.

Internal influence subsystem—The more investors learn about the new technology through internal factors, the more they spread W-o-M, which enhances the "attitude in favour". For internal factors to be effective, potential adopters must have access to readily available, comprehensible information. Not every exposure to scientific and economic facts by "Potential investors" will be adequate. Thus, the number of potential investors from W-O-M is a function of the "Attitude in favour," i.e., convincing arguments soundly support it.

Awareness subsystem—Exposing the public and investors to technology would not necessarily reduce their reluctance to accept it. The public is concerned about safety and effectiveness, while investors consider returns on their investments and the impact of public protests. However, remaining vocal sceptics is a primary predictor of lack of willingness to accept, which represents the main "adoption barrier" for the first time in the model.

Internal and external are not taken as synonyms for intrinsic and extrinsic in this paper. The word intrinsic means a 'fundamental or inseparable property of', whereas internal in this sense means 'emanating from within'. So, an intrinsic influence is an inseparable property of the activity itself, such as 'learning' or the product of that activity, such as model building. In contrast, an internal is the feeling of insight that arises in the person who completes or engages in the activity.

The model distinguishes between investors who are willing to accept the technology in principle ("Investors") and those who are likely to adopt CCS when it establishes itself ("Potential investors").

To adopt a specific technology, investors must become aware of it and be comfortable with it, thereby reducing uncertainty. Learning can influence adoption. Awareness would influence motivation and put fear barriers into perspective. Increasing the awareness of the entire investing population, "average investors' familiarity," would somewhat overcome the adoption barrier. Making investors aware of the technology through education enables a realistic understanding of their perceived risks, which could reduce the likelihood of reaching incorrect conclusions, such as the "average expectation of profitability". On the other hand, exposure could increase "average learning", facilitating the mitigation of reluctance about the technology's suitability. For adoption to occur, there must be evidence that technology delivers its promises. This requires objective technical experts. Therefore, the "average confidence in technology" directly affects the adoption rate.

For adoption to be possible, it is necessary that appropriate technology is available and that there are no obstacles to its transfer. The variable "Availability of state support" assumes that it is adopted from the beginning of 2000. It is a step function that requires a start date for the state support to take effect.

It is worth noting that certain underlying assumptions can impact the model in Figure 3. These assumptions are:

- It is assumed that investors who have gained knowledge about the suitability and profitability of the technology either embrace or reject it. Some investors only touch well-established (blue chip) industries and never consider CCS,

- The "average confidence in technology is the average penetration of the technology estimated based on published papers.
- Factors, such as the effect of the investor's brand (player behind the brand), type of technology, alternatives, image, and price, are omitted from consideration. This separates the adoption from the investment flows.
- Some variables have not been included in the model because their influence is not significant, and ignoring them makes the model less crowded. For example, eco-protesters frequently put themselves in harm's way to convey the urgency of addressing carbon emissions, a strategy that has proven ineffective. The strongest predictor of willingness to pay the cost is the perceived immediacy of danger. Nevertheless, the concept of eco-consciousness is indirectly present, as the model includes data on public awareness and acceptance.

A brief qualitative sensitivity analysis was conducted to examine the influence of the assumed behavioural parameters, including positive word of mouth (W-o-M), the Fraction of potential investors encouraged by advocacy group activities, Average confidence in technology, and the likelihood to invest. These variables were initially assigned assumed values based on logical reasoning and the behavioural diffusion literature, given the insufficient real-world data currently available for the CCS context.

Due to the scarcity of quantitative data, this paper employs linguistic variables. Linguistic Variables are terms or concepts whose values are not numerical but are expressed in words or phrases from a natural language. A linguistic variable is either a language variation that involves "two or more ways of saying the same thing" as employed in fuzzy logic systems whose values are words or sentences, not numbers. Linguistic variables are used to represent imprecise or human-like concepts, such as speed being "slow," "medium," or "fast," where each term corresponds to a range (See Table A1 in the Appendix A). In computational and social sciences, these variables allow for the modelling of systems where precise numerical measurement is difficult. They are crucial for representing subjective or qualitative data.

We examined three distinct scenarios to investigate how different factors would influence the technology penetration. All factors are normalised to a 0–1 scale, facilitating easier comparisons, improved model stability, and more straightforward interpretation. Appendix A shows the scaling method used. Each case study shows how behavioural and perceptual variables influence the technology adoption process. Examining different conditions reveals the behavioural factors most critical to successful technology adoption, offering guidance to improve reliability and acceptance.

3. Results

3.1. The SD Model of CCS

The proposed framework (Figure 2) was employed to identify relevant variables and their causal relationships. The system boundary, as shown in Figure 2, is used as the backbone of the proposed SD model. Figure 3 shows an SD model of Figure 2 in Vensim PLE, which is an extended version of Figure 1, in turn based on Bass' idea [54]. Tables 2–6 presents the expressions for all stocks, flows, and auxiliary variables, along with their definitions, units, and estimated values.

Table 2. Stocks.

Stock	Description	Equation	Unit
Investing population	Investors who finance enterprises	=INTEG (−potential investor rate) + [Total possible investors]	People
Potential Investors	Investors who are likely to consider CCS technology	=INTERG (Potential investors rate-Investors rate-Rejections rate, 0)	People
Investors	Investors worldwide are likely to invest in CCS technology.	=INTEG (Investors rate − Rate of market leavers, 150)	People
Rejectors	Investors in the world who are likely to invest in CCS after becoming aware of it	=INTEG (Rejection rate + Rate of market leavers,0)	People

Table 3. Flows.

Flows	Description	Equation	Unit
potential investment rate	Number of first-time investors in CCS/near	=Attitude in favour + Potential investors from advocacy group activities	people/Year
Investor rate	The likely number of people who would invest in CCS per year	=(Potential Investors × likelihood to invest) × Availability of state support × Fraction of confidence in adoption × Productivity	people/Year
rejection rate	investors who are likely to reject the CCS technology/year	(1 − Likelihood to invest) × Potential Investors × (1-Fraction of confidence in adoption) × Availability of state support × Productivity.	people/Year
Rate of market leavers	Number of investors who are likely to withdraw from the CCS market per year	=1 − Likelihood of a reasonable rate of return on investment	people/Year

Table 4. Auxiliary variables with lookups.

Auxiliary Variables	Description	Equation	Description
Average investors familiarity	Average awareness of the total investing population in CCS technology as a percentage of investors who considered investing	((Total possible investors-Investing population)/Total possible investors)	Dmnl
Adoption barrier	Average learning + average profitability expectation. 0 for the total barrier, and 1 for no barrier at all.	1 − (Average expectation of profitability/2 + Average learning/2)	Dmnl
Potential investors from advocacy group activities	The number of potential investors who are likely to invest as encouraged by promotional activities	=Investing population × Investors' hesitation × Fraction of potential investors encouraged by advocacy group activities	people/Year
Attitude in favour	The number of potential investors who are likely to invest as encouraged by word-of-mouth	(Investing population × Positive W-O-M × Average investors familiarity) × Investors hesitation × Technology Performance	people/Year

Table 5. Look-up table for some auxiliary variables.

Auxiliary Variables	Description	Equation	Description
Average expectation of profitability	Average profitability expectation of the population regarding CCS profitability	=WITH LOOKUP (Average investors' familiarity, ([(0, 0)–(1, 1)],(0, 0.2),(0.5, 0.43),(1, 0.55))	Dmnl
Average learning	Average learning of investors regarding technology.	=WITH LOOKUP (Average investors familiarity, ([(0, 0)–(1, 1)],(0, 0.01),(0.25, 0.33),(0.5, 0.57),(1, 0.7))	Dmnl
Investors hesitation	Hesitation to invest is assumed to be a function of investors' average hesitation. 0 for the full barrier, and 1 for no barrier	=WITH LOOKUP (average hesitation level, ([(0, 0)–(1, 1)],(0, 1),(0.3, 0.9),(0.6, 0.56),(1, 0)))	Dmnl
Likelihood to invest	Likelihood to invest in CCS, because of the barrier to adoption. 0 for no barrier, and 1 for the total barrier.	=WITH LOOKUP (Adoption barrier, ([(0, 0)–(1, 1)], (0, 1), (0.55, 0.12), (1, 0))	Dmnl
Fraction of confidence in adoption	A fraction of investors adopt CCS because they like its goals. 0 for no adoption, and 1 for full adoption.	=WITH LOOKUP (Average confidence in technology, ([(0, 0)–(1, 1)],(0, 0),(0.125, 0), ((0.4, 0.24),(0.6, 0.5),(0.74, 0.7),(0.875, 0.95), (1, 1))	1/Year

Not all the data required for this model are readily available; thus, we made some assumptions. For example, the "Positive W-o-M", the "fraction of potential investors from advocacy group activities", and "Attitude in favour" are assumed values and hence should be understood in this context. These variables influence the value of the "average investors familiarity". They determine the number of individuals in the investing population who had the opportunity to participate in the investment. The numerical values of these variables have been adjusted so that the system reached an average investor familiarity level of approximately 20% in 2020. Values of both variables were adjusted for the cumulative internal influence (number of "Potential investors" at the end of the simulation, because of internal influence) to be approximately ten times bigger than the cumulative external influence (number of "Investing population" at the end of the simulation, because of external influence)

Several tests were conducted to investigate the system's structural and behavioural characteristics.

- Variables were set at their extreme values to study the consistency and significance of their behaviour.
- Correct choice of the model boundaries was confirmed by discussion with the subject experts.
- Logical consistency
- Dimensions Consistency:

Table 6. Constants.

Constants	Description	Equation	Unit
Availability of state support	The variable that represents the availability of subsidies in CCS 0 before the year 2000, and 1 from the year 2000	=STEP (1, 2000)	Dmnl
Average hesitation	The average level of hesitation among investors when considering investing in CCS is. On a scale of 0 to 1.	0.32	Dmnl
Average confidence in technology	The process of "Average confidence in technology" was normalised to 0–1.0.	0.35	Dmnl
Likelihood of a good rate of return on investment		0.7	Dmnl
Technology Performance		0.8	Dmnl
Fraction of potential investors encouraged by advocacy group activities.	Percentage of potential adopters exposed to the CCS advocacy group promotional activities	0.0036	1/year
Positive W-O-M	The likelihood that word-of-mouth by other adopters would result in adoption	0.151	Dmnl
Total possible investors	The total population in the model indicates the total number of investing individuals	$1 \times 10^6 - (10^6 \times 0.04)$	people
Productivity	This variable indicates if the technology is mature for deployment. 1 if the answer is yes. 0 is not productivity at all, and 1 is maximum productivity	0.75	Dmnl

3.2. Base Case

Figure 5 presents variations in the values of stocks from the year 2000 to 2080. Advocacy groups started promoting CCS in the early 2000s [55]. However, the start date cannot be precisely pinpointed; hence, 2000 is assumed to be the starting point. Earlier, a group of oil companies chose to explore injecting CO_2 into an active oil field as a complementary approach to enhance production. Their objective was to extract a higher proportion of the oil reserves in the reservoir [56]. Approximately 80 years of CCS adoption have been conducted. Simulation reaches a steady state at the end of this period. Following the original Bass theory, Changes in the investors' population in this period were ignored [9]. This simplifying assumption removes unnecessary complications from the simulation, focusing on replicating the adoption curve's shape rather than its final values.

As seen in Figure 5, the diffusion process of CCS technology begins slowly, with the stock of "Potential Investors" gradually decreasing. At the beginning of the simulation, external influences and advocacy groups' activities are the primary mechanism that reduces the stock of "Potential investors". Through these activities, a certain number of investors become aware of CCS technology each year, gradually increasing the "Investing population". In turn, the "Investing population" increases the likelihood of adoption through word of mouth, thereby positively affecting "Average investors' familiarity."

The impact of W-o-M (i.e., internal influences) intensifies over time, eventually becoming the primary adoption mechanism and accelerating the decline of the "Investing population" stock from about 2020. By the depletion of the "Investing population" stock around 2070, the effectiveness of both mechanisms fades as the fresh “Investing population” is depleted. Everyone is aware of the goal to achieve CCS by 2080.

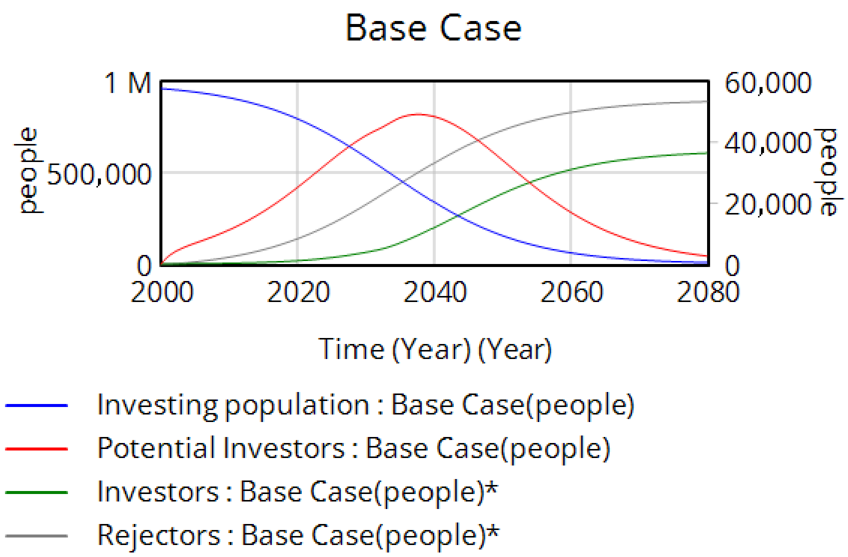


Figure 5. Base case—changes in the stocks during the 80-year simulation. It can be seen that the diffusion process of CCS technology begins slowly, with the stock of “Potential Investors” gradually decreasing. Variables without (*) means they are plotted on the primary *Y*-axis (left-hand side) and variables with (*) indicates that the variable is plotted on the secondary *Y*-axis (right-hand axis). The variables have very different scale.

As technology becomes commonplace, the “Potential investors” and “Rejecters” stocks start to fill with individuals aware of CCS technology. The end of the simulation shows many people in the “Rejecters’” stock, and correspondingly fewer people in the “Potential investors’” stock, indicating that the total adoption is not soaring. Adoption is, to some extent, affected by the “likelihood to invest” due to the “Average expectation of profitability” and “Average learning” of the technology amongst investors exposed to it. As average investors become more familiar with technology, the likelihood of investing in it will also rise. Despite the rise in average investors’ familiarity having a favourable impact on the likelihood of adopting investing, its influence is not high in the simulation, indicating entrenched barriers to accepting CCS.

In addition to the low likelihood of investing in adoption, the rejection process, which is dependent on the “average learning,” is another challenge for the adoption process. Currently, the likelihood of a good return on investment in CCS projects is not attractive to investors. The likelihood of a reasonable rate of return on investment, availability of state support, and a stable regulatory regime are primary factors in deciding to invest in CCS. Positioning CCS among wind and solar energy encourages consumers to compare them economically, expecting the unit price of electricity to be similar. Some “Investing population” may leave the market if the initial experiences disappoint them.

The base case indicated that the diffusion of CCS technology requires substantial time for the number of “Investors” to rise. The adoption of CCS has begun relatively recently, and it will take many years for everyone to become aware of its benefits, assuming the technology continues to improve and is promoted.

3.3. Cases

Table 7 presents three groups of cases to examine the impact of modifying specific variables on the simulation results. Only one or two variables were changed in each sicario to avoid complexity and to understand the connections between the variables and the model behaviour.

Table 7. The cases and scenario analysis.

Cases	Description	Value of Variable
Case 1	Case 1 examines the influence of advocacy groups' activities and the extent of W-O-M relative to the base case. **(Case 1-1)** The value of the "Positive W-o-M" was increased by 10% from 2000 to 2080. **(Case 1-2)** Both "Positive W-o-M" and "Potential investors from advocacy group activities" were increased by 10% and 100% respectively, from the year 2000 to 2080 (when the technology became widespread	**(Case1-1)** "Positive W-o-M" = 0.151 + STEP (0.151 × 1.1, 2000) (1/Year) **(Case 1-2)** "Fraction of potential investors encouraged by advocacy group activities" = 0.0036 + STEP (0.0036 × 2, 2000) (1/Year). "Positive W-o-M" = 0.151 + STEP (0.151 × 1.1, 2000) (1/Year)
Case 2	S2 examines the impact of slow (**Case2-1**) Moreover, a sudden increase in the learning process is observed (Case2-2) compared to the base case. In **Case 2-1**, the value of the "average learning" variable was increased linearly from 2015 to 2080. In **Case 2-2**, all increases are immediate.	**(Case2-1)** = "Average confidence in technology". 0.35 until 2015, then linear growth from 0.35 in 2015 to 0.8 in the year 2080. (Dmnl) **(Case2-2)** 0.8 from the year 2020 (Dmnl)
Case 3	Case 3 examines the effect of changing the "Likelihood to invest" in the rate of adoption. The variable In (**Case 3-1**), "Likelihood to invest" was changed, and the results are compared with the base case. In (**Case 3-2)**, the likelihood of investing and learning processes was increased.	**(Case 3-1)** "likelihood to invest" = WITH LOOKUP (adoption barrier, ([(0, 0)–(1, 1)], (0, 1), (0.55, 0.19), (1, 0)) (Dmnl) **(Case3-2)** "Likelihood to invest" is the same as in Case 3-1, and "average confidence in technology" is the same as in Case 2-2. (Dmnl)

Case 1 aims to determine whether increasing internal and external influences impact adoption compared to the base case. The "Fraction of potential investors encouraged by advocacy group activities" variable is not very sensitive (see Case 1 in Figure 6); hence, Case1-1 shows that only the "Positive W-O-M" was increased. Similarly, Case 1-2 examines the effect of increasing both advocacy group promotions and positive Word-of-Mouth. Increasing W-O-M (Case1-1) accelerates the rate of reduction in the "Investing population" (a stock), compared to the base case, thereby increasing the adoption rate. The adoption rates are low in both Case 1-1 and Case 1-2. This can be partially attributed to the low familiarity with CCS technology and the high adoption barriers ("Average expectation of profitability" and "Average learning"), which directly result in a low "likelihood to invest". When the internal and external influences were increased (Case1-2), no appreciable change in adoption rate was observed, compared with Case 1-1. Possibly, the advocacy group activities might have a favourable effect on the willingness to invest in technology, although they may not be fully aware of it. Promotion is an effective lever to build widespread familiarity at the start of the adoption process, thereby contributing to overall technology acceptance.

Case 2 examines the effect of state intervention on model behaviour (Case 2-1 and Case 2-2) relative to the base case. Case 2-1 assumes that the increase in state support is measured, and the level of the "average learning of the" variable will linearly increase from 2000 to 2080. Case 2-2 examines the adoption of a mature technology from 2020. An increase in the total adoption rate was observed in two cases. Continued cost reduction in the technology could accelerate adoption rates. This effect is more pronounced when productivity improvement is immediate. Results in Case 2 show that improving technology's productivity is paramount. The longer the public is exposed to an emission problem that does not feel urgent, the more cumulative the rejection becomes.

Case 3 examines how altering the "likelihood to invest" affects the results. The likelihood of investing has been assessed through the willingness to invest in technology. Case 3-1 uses high values to compare it with the base case. An immediate increase in average confidence in the technology was implemented in Case 3-2. The value of the "likelihood to invest" in Case 3-1 and Case 3-2 is larger than in the base case by a factor of 1.6. Figure 6 demonstrates the effect of changing the value of "likelihood to invest" (Case 3-1). This can increase investment outcomes, though not to the same extent. The "Adoption barrier", resulting from a lack of awareness, uncertainties, and unfavourable feelings, can directly impact the "likelihood to invest". To significantly improve the change in investment rate, the combination of the "likelihood to invest" and average confidence in the technology must be increased (Case 3-2). Case 3 examines how past experiences influence investment in such technology. Experience forms perceptions that do not alter quickly. However, incentives such as higher productivity, higher prices, and tax exemptions can positively influence adoption.

Cases 2 and 3 illustrate the impact of the "Average confidence in the technology" on behaviour, which remains unchanged at the "Investor population" level. The Bass model ignores the impact of unfavourable W-o-M; even with this omission, the model captures historical behaviour quite well.

Case 1

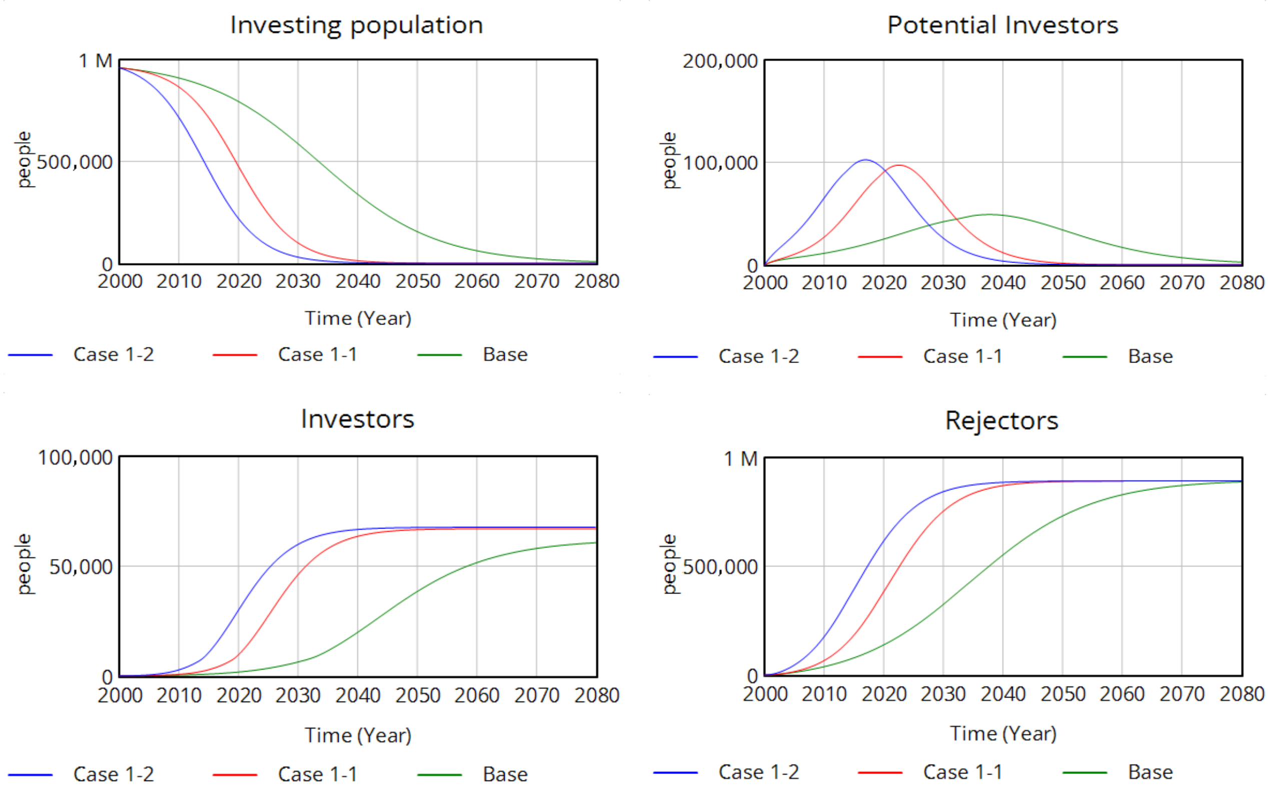
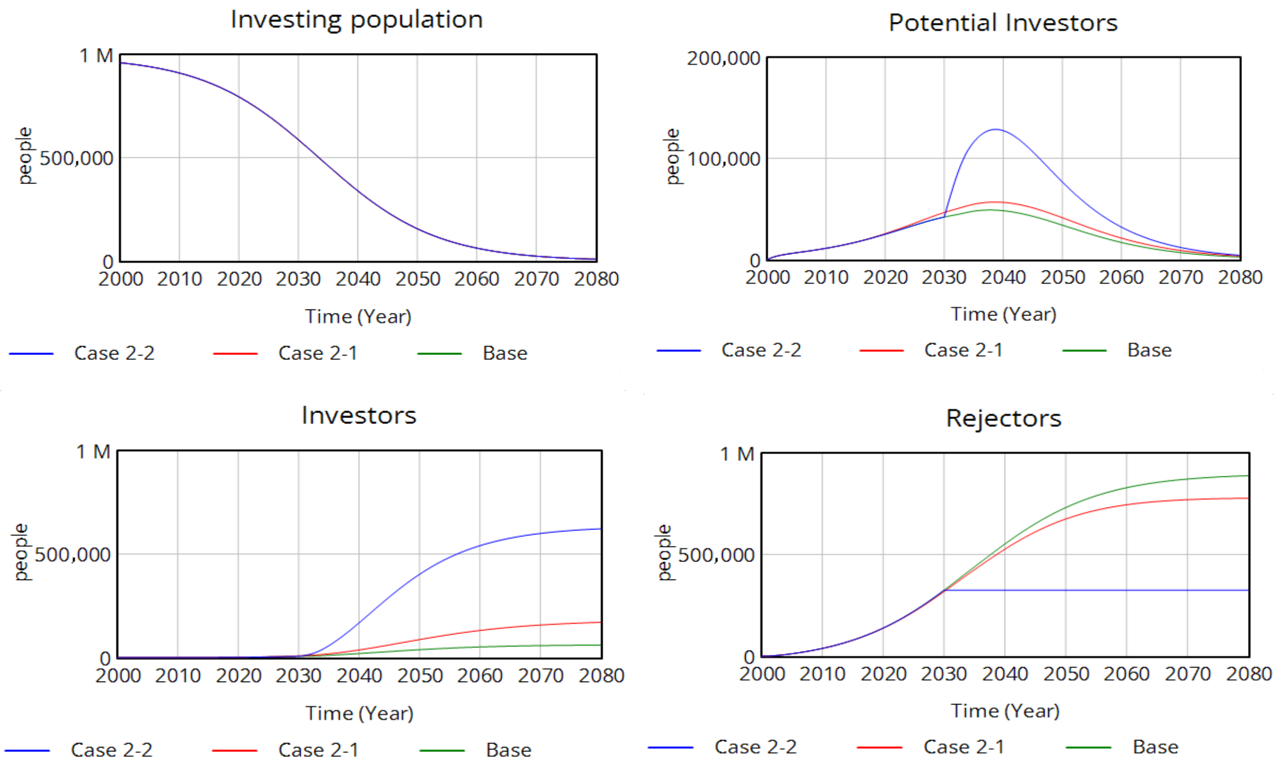


Figure 6. *Cont.*

Case 2



Case 3

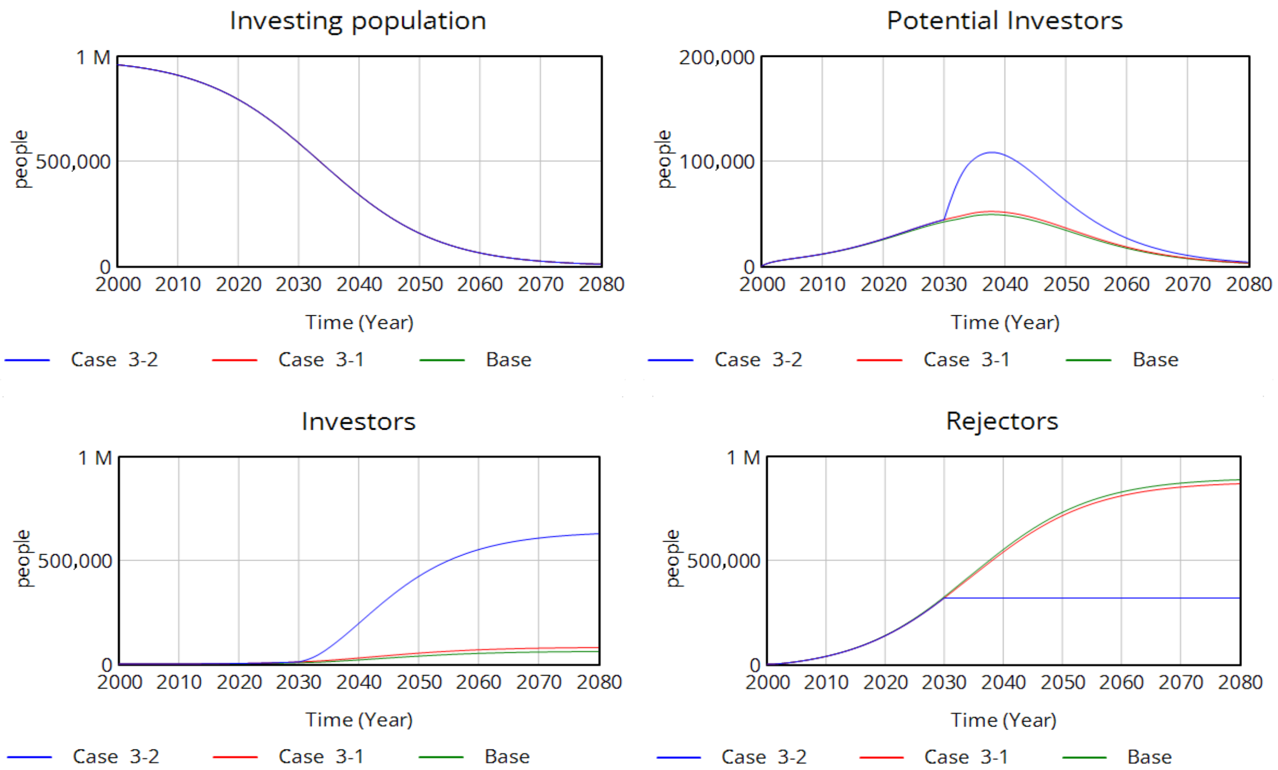


Figure 6. Changes in the stock variable "Investors population"," Potential investors", "Investors", and "Rejecters" (three scenarios). (**Case 1**): Enhancement of internal and external influences. (**Case 2**): Enhancement of average confidence in the technology. (**Case 3**): Increase in investment likelihood.

As shown in 6, the model results indicate measurable sensitivity to behavioural factors. For instance, a 10% rise in "Positive Word of Mouth (W-o-M)" leads to approximately

30 years earlier full investment, whereas if a 100% increase in "Potential investors from advocacy group activities" at the same time, equivalent would lead to 35 years earlier full investment of 1 million population. When it comes to potential investors, a 10% increase in positive W-o-M leads to sharp rise to 98,000 in 2023 with a rapid decline. In contrast, if a 100% increase in "Potential investors from advocacy group activities" at the same time is added then the potential investors peaks around 2017 at over 100,000 people compared to the base case where there is a gradual increases from 2000, that peaks around 2040 at almost 50,000 people, and then slowly decreases which shows a slow and prolonged potential investment. The number of investors would reach its maximum of 67,000 people earlier in 2035, with a 10% increase in positive W-o-M and a 100% increase in potential investors from advocacy groups. This maximum can be reached in 2040 if there is only a 10% increase in word of mouth. The base case here shows a maximum of 60,000 investors by 2075. Both positive behavioural changes show that the rejectors rise fastest, reaching a maximum by 2035, while word of mouth increases peaks around 2040. The Base scenario grows slower, reaching similar levels only by 2070.

As shown in Figure 6, a 129% rise in "Average confidence in technology," whether gradual from 2015 to 2080 or sudden beginning in 2020, results in no change from the baseline outcome, where the total investing population remains fixed at one million. Across all scenarios, the number of potential investors increases from 2000, peaks between 2035 and 2040, and then declines toward zero by 2080. In the base case, the peak is about 50,000; with gradual increases in confidence, it rises to roughly 58,000; and with sudden increases, it reaches around 130,000. Only the sudden increase scenario shows a notable deviation around 2030, possibly because a sharp rise in confidence accelerates early adoption. After 2040, however, all curves decline, suggesting a stage of technological maturity. The number of "Investors" also grows throughout the simulation period. All scenarios remain close to zero until about 2030, after which they diverge. By 2080, the base case reaches about 65,000 investors, the gradual increase scenario about 220,000, and the sudden increase scenario around 630,000. In the sudden increased case, investor growth is most rapid between 2030 and 2060, stabilising thereafter. For "Rejectors," all scenarios start near zero and rise to approximately 350,000 people by 2030. Beyond this point, they diverge: the sudden increase scenario levels off around 350,000 through 2080, the gradual increase continues more moderately to about 700,000, and the base case grows the most, reaching around 850,000 by 2080. Relative to the base case, the sudden increase leads to early stabilisation near 2030 levels, while the gradual increase produces an intermediate trend.

This scenario-based analysis shows how group populations shift toward investors or rejectors when there is a change in "likelihood to invest," and another scenario in which this change occurs simultaneously with a sudden increase in "average confidence in technology." In the Base case and the scenarios, the flows and outcomes differ. Two changes that occur simultaneously drive many potential investors to convert, keeping rejectors flat. The other two convert fewer and end with far more rejectors. Potential investors peak in the second case, with approximately 110,000 people, versus approximately 43,000 people in the others, aligning with investor counts growing to approximately 600,000 versus almost 85,000 by 2080. The two simultaneous changes also cap rejectors near 350,000 by 2030–2080, while Base and change "likelihood to invest" changes to approximately 910,000. The investing population shrinks from 1 million to near zero by 2080, while crossing 500,000 around 2030. The second case shifts transitions toward investors and reduces the number of rejectors; the base case and first scenario channel more people into rejectors. The 350,000 rejector plateau suggests a ceiling in the second scenario, while the others follow an S-curve, accelerating at the beginning and then slowing. By the end, second scenario yields almost 600,000 investors versus 85,000 elsewhere, with 350,000 rejectors versus approximately 920,000. Differences begin to appear around 2030, when both scenarios diverge from the others, indicating a possible turning point driven by behavioural and policy factors.

One should be aware that innovation acceptance models are not predictive tools, but rather descriptive ones designed to give a sense of what the future for a product might be. If reliable data are available (which is not for CCS), its depiction of the future would be more accurate. The presented scenarios are just a demonstration of how the model works.

4. Discussion

The purpose is to extend the Bass diffusion model to explore pathways to CCS acceptance and, ultimately, adoption. The CCS diffusion is a complex, path-dependent dynamic problem, in which several mutual feedback loops between primary variables may exist, as technology diffusion requires an extended time horizon, and such relationships are subject to change.

This proposed framework has some limitations because of a lack of reliable data. Consequently, until better data become available, it is worth considering how the future might unfold. It can help provide insight into trends in CCS adoption and identify areas where to focus to accelerate CCS acceptance. The lack of data regarding the investor population, the influence of advocacy efforts or W-O-M on investors and the public, and the learning process over time are based on expert judges, along with a few other variables. Experts bring their own experience and knowledge, but their judgment may be hype or hope. Expert biases do not hinder the fundamental understanding of Carbon Capture diffusion behaviour; however, for precise predictions of the system's behaviour, these data must be evaluated with greater accuracy. Because, under different circumstances, the diffusion of CCS might take a different path.

Researchers rarely address return on investment, and we were unable to fully incorporate it into this study due to a lack of applicable data and uncertainty about the price of carbon pollution in the open market. Moreover, other knowledge gaps require the attention of researchers.

The reasoning processes and psychology of investors influence their decisions, whereas SD does not fully account for variations in individual investors' decision-making outcomes. The SD method is an aggregate approach in which investors are assumed to be a perfectly mixed group of individuals with similar attitudes who exhibit average behaviour. However, it is possible to divide investors into distinct groups with distinct behavioural characteristics, which are not explored in this study.

The goal is to highlight the utilisation of the system dynamics approach for simulation in studying broader dynamics of carbon capture in a free market. SD does not determine the exact number of adopters, but it helps identify trends while accounting for underlying mechanisms. The SD models can help policymakers develop effective policies by testing the effectiveness and consequences of various strategies over time, informing future policy decisions. The SD approach can facilitate the development of potentially successful emission control policies.

From a diffusion-of-technology perspective, the CCS is a closed system in which output influences input. This means the system's performance depends on its past performance, as shown in causal loops in SD. The starting point for building an SD model is identifying the system's variables, their relationships, and their respective strengths. These variables influence the system's behaviour by creating a feedback loop. "Positive or negative directions of feedback are indicated by a plus or minus sign, indicating the influence direction [8]." The dynamic interaction between the parameters governing a system can lead to different types of behaviour, such as lockout or bridging, phasing out, or the diffusion of one or more individual technologies. Alternatively, the coexistence of two or more technologies may occur.

Opportunities and New Directions

The system dynamics approach is well-suited for addressing dynamically complex issues, such as diffusion processes. SD has made significant contributions to understanding the diffusion of innovations, infections, and error propagation, and to their management. There is much more to explore in understanding the dynamics of individuals' acceptance of novel technologies. SD could also address multiple interacting influencing parameters, leading to a better picture of the policy implications of adopting a suitable value for them.

The exploratory SD model described in this paper has shown that it can address issues in diffusion processes. SD concept can assist government and private investors in understanding the level of coordination required to implement climate change and CO_2 reduction policies without overwhelming national governments' resources. SD models could also examine the potential contribution of all energy delivery methods, such as wind or solar. The more comprehensive view of the entire energy system's dynamics described here could also facilitate the delivery of cleaner energy at an international level. Examples include the large unreported polluters, high energy costs, and the scarcity of funds. System dynamics can help identify the feedback loops responsible for such issues and illuminate the path towards strategies that benefit the Earth's inhabitants.

The proposed framework is descriptive, not predictive, primarily because the data are descriptive. Although the model is complete and produces reasonable results for CCS in different contexts, the lack of quantitative data for CCS impacts the ability to make sensible predictions. One should not expect exquisite precision when using imprecise input.

5. Conclusions

A system dynamics model was developed using several variables selected from a broad range of control variables, based on a literature review and interviews with field experts. Models that replicate reality in its entirety require hundreds of variables and their relationships, along with reliable numerical values. This process involves hypothesis formulation, scope selection, causality identification, variable quantification, sense-making (reality checks), testing, verification, validation, and what-if analysis. The refinement continues until the model replicates reasonable historical patterns and provides usable insights regarding future trends.

An SD approach is described to explore the path to carbon capture acceptance. The primary objective was to identify and study the effects of various variables influencing technology, while accounting for resource constraints, causal relationships, feedback, and the delayed effects of chosen policies. The conclusion drawn from a limited scenario analysis indicates that the model can help advocacy groups and governments analyse their initiatives before implementation. This approach helps study the consequences of various strategies to determine a workable policy. SD helps develop strategic thinking for policy development and fosters a shared understanding and insights for collaboration between advocacy groups and those responsible for developing emission control policies. What-if analysis, which involves varying parameters, provides a straightforward way to understand the implications of different policies. There are numerous policy decision situations where the system dynamics approach could be used to explore the possible impacts of different decisions. Future studies may reveal how this model can be refined to enhance strategic decision-making.

A sensitivity check was performed on the model to ensure that its outcomes remain unaffected by changes to the most uncertain data, thereby validating its usefulness. However, some uncertainties could influence the result. The model enables policymakers to identify key areas and focus their attention accordingly.

The primary aim was to present a framework for studying the impact of various variables on the adoption of carbon technology. Based on an extensive literature review, suitable parameters were selected to enhance the model output. All model equations are provided in this paper for those who wish to replicate our results or apply them to their own data. The main conclusions are:

- Realistic modelling of CCS adoption from endogenising political and social factors.
- A measure typology enables modelling how measures spread, considering various influencing factors.
- Model feedback between CCS technology, public perception, market reaction, and implementation.
- Concepts of political will and public willingness to participate are used in the model.

Further studies could examine several areas beyond the present work. This study used only a single policy step introduced in 2000, but it would be beneficial to examine different policy changes, such as gradual increases or on-and-off cycles. We also focused only on positive word-of-mouth (W-o-M), which represents overall support, but including negative W-o-M could help with public uncertainty and show how it might influence the growth of the "Rejecters" group and overall adoption. Finally, the study considers a single, standardised market, whereas further studies could examine multiple market structures, including individual and institutional investors, to understand how institutional participation might alter the market.

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Abbreviations

The following abbreviations are used in this manuscript:

A	Adopters
AR	Adoption Rate
B	Balancing loop
CCS	Carbon Capture and Storage
CO_2	Carbon Dioxide
N	Total population
P	Potential adopters
R	Reinforcing feedback loop
SD	System Dynamics
STT	Socio-Technical Transition
W-o-M	Word of Mouth

Appendix A

Table A1. Linguistics definition of constants and their numerical values.

Variable	Linguistic Definition	Numerical Definition	Reference Condition
Availability of state support (on a scale of 0 to 1)	Low	0–0.25	0.32
	Medium	0.26–0.50	
	High	0.51–0.75	
	Very high	0.76–1.0	
Average hesitation (on a scale of 0 to 1)	Low	0–0.25	0.32
	Medium	0.26–0.50	
	High	0.51–0.75	
	Very high	0.76–1.0	
Average confidence in technology (on a scale of 0 to 1)	Poor	0–0.25	0.35
	Average	0.26–0.50	
	Good	0.51–0.75	
	Excellent	0.76–1.00	
Likelihood of a good rate of return on investment (on a scale of 0 to 1)	Poor	0–0.25	0.7
	Average	0.26–0.50	
	Good	0.51–0.75	
	Excellent	0.76–1.00	
Technology Performance (on a scale of 0 to 1)	Weak	0.00–0.35	0.8
	Average	0.36–0.70	
	Excellent	0.71–1.00	
Fraction of potential investors encouraged by advocacy group activities.	From the consensus of expert opinion		0.0036
Positive W-O-M (on a scale of 0 to 1)	Poor	0.1–0.3	0.151
	Not bad	0.4–0.6	
	Good	0.7–0.8	
	Excellent	0.9–1	
Productivity (on a scale of 0 to 1)	Poor	0.1–0.3	0.75
	Not bad	0.4–0.6	
	Good	0.7–0.8	
	Excellent	0.9–1	

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